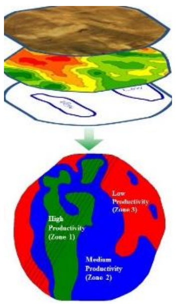
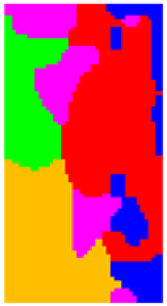
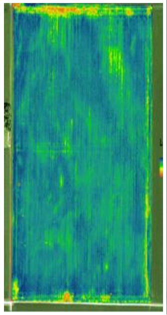
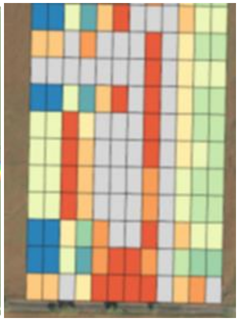
Advanced Crop Advisors Workshop, Feb. 11-12, 2020

Development of Management Zones and the Use of Proximal/Remote Sensing for Site-Specific Nutrient Management

Dr. Yuxin Miao

Precision Agriculture Center
Dept. of Soil, Water and Climate
University of Minnesota

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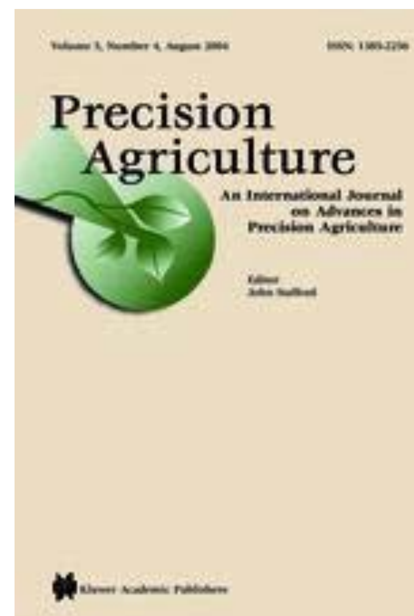
Precision Agriculture Center

Precision Agriculture was started at the U of M in the early 1980s

U of M founded the International Conference on Precision Agriculture in 1992

The first Precision Agriculture Center in the world was established at the U of M in 1995

U of M founded the Precision Agriculture journal in 2000



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precision conservation, environmental quality
remote sensing

Associate Director, Dr. Yuxin Miao

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integrated precision crop management
remote sensing

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Soil-landscape analysis

Dr. Fabian Fernandez

Nutrient management and water quality research and extension

Dr. Daniel Kaiser

Nutrient management research and extension

Dr. Carl Rosen

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Dr. Vasudha Sharma

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Dr. Candice Hirsch  High throughput phenotyping, hyperspectral remote sensing

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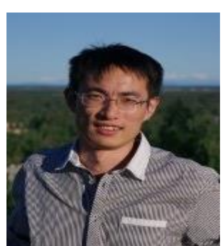

Crop growth modeling, remote sensing

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Dr. Shashi Shekhar		Spatial computing, data mining, parallel computing
Dr. Nikolaos Papanikolopoulos		Computer vision

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Integrated pest management in soybean, environmental and economic sustainability

Dr. Ian MacRae

Site-specific integrated pest management, landscape ecology, GIS, spatial statistics

Dept. of Forest Resources

Dr. Joseph Knight

Remote sensing and geospatial analysis, land use impacts on environment and natural resources

Dept. of Plant Pathology

Dr. Cory Hirsch

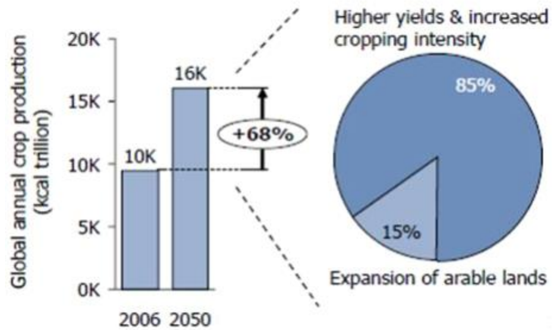
Phenotypic information to understand abiotic and biotic stresses

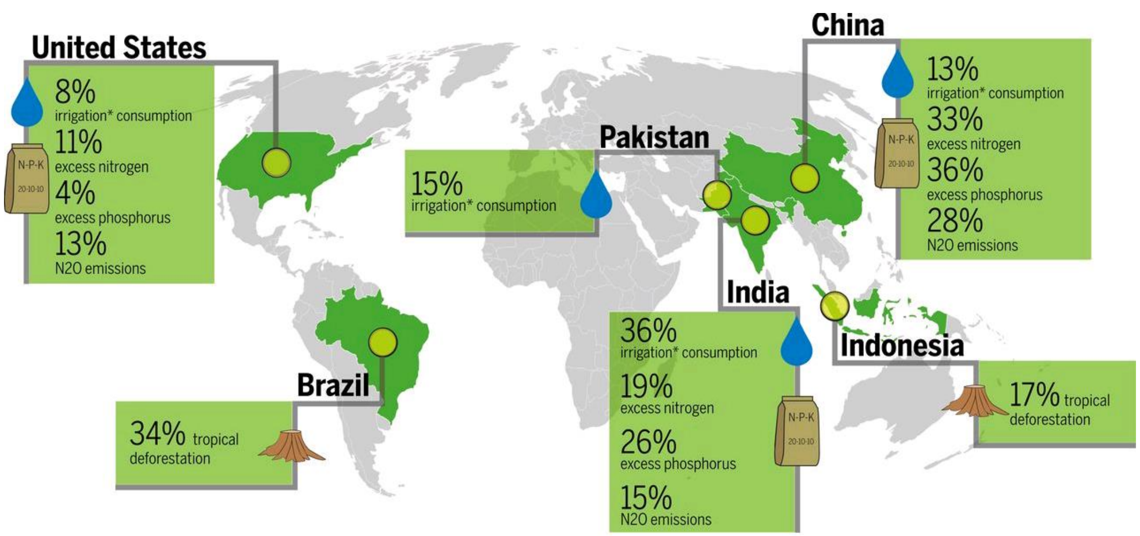
Dept. of Aerospace Engineering & Mechanics

Dr.Demoz Gebre-Egziabher

Navigation, guidance, and control of aerospace vehicles, image georegistration

Challenges of World Agriculture





Food Security

Resource Use Efficiency

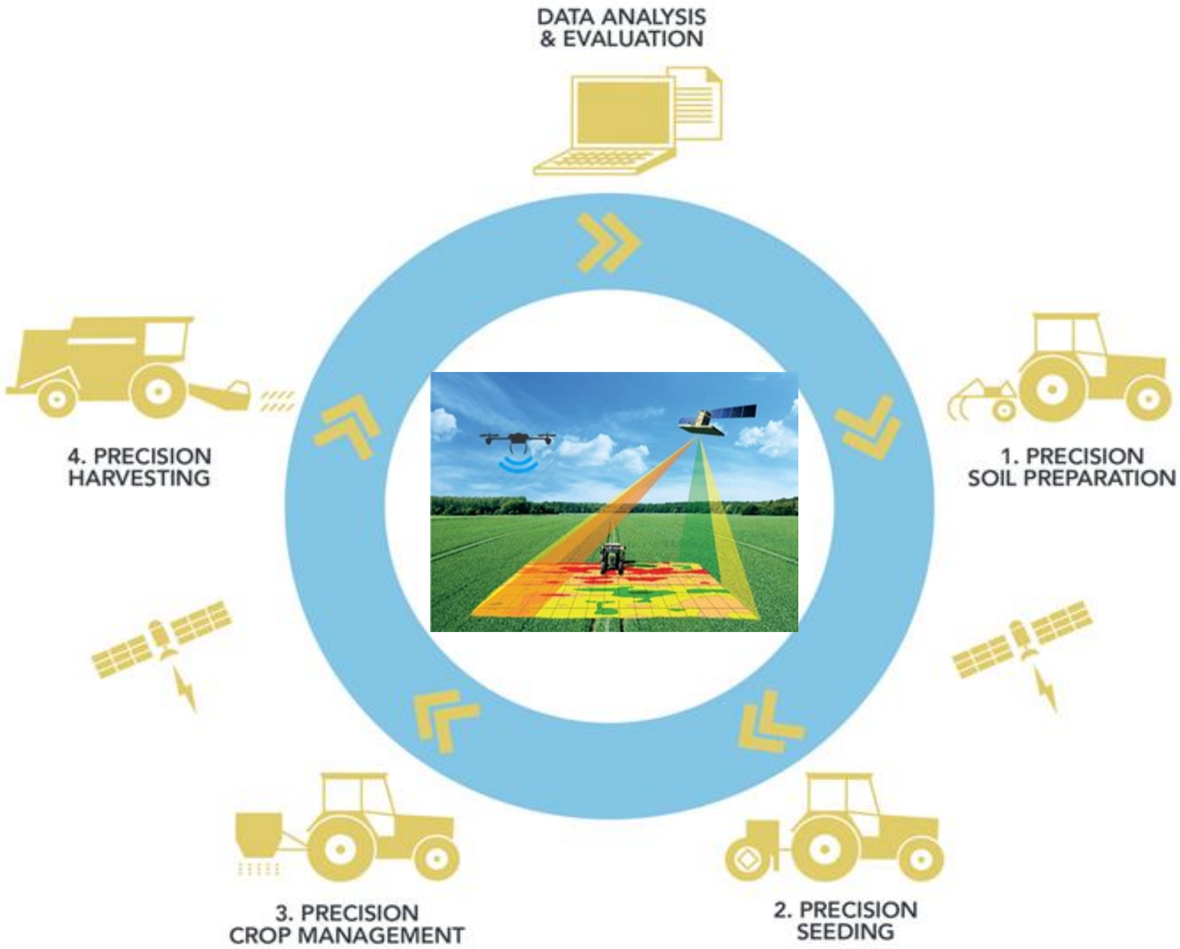
Environmental Protection

Increase profitability

Climate Change

Foley et al. 2011; FAO "How to Feed the World 2050"; West et al., 2014

Precision Agriculture



The next agricultural revolution!

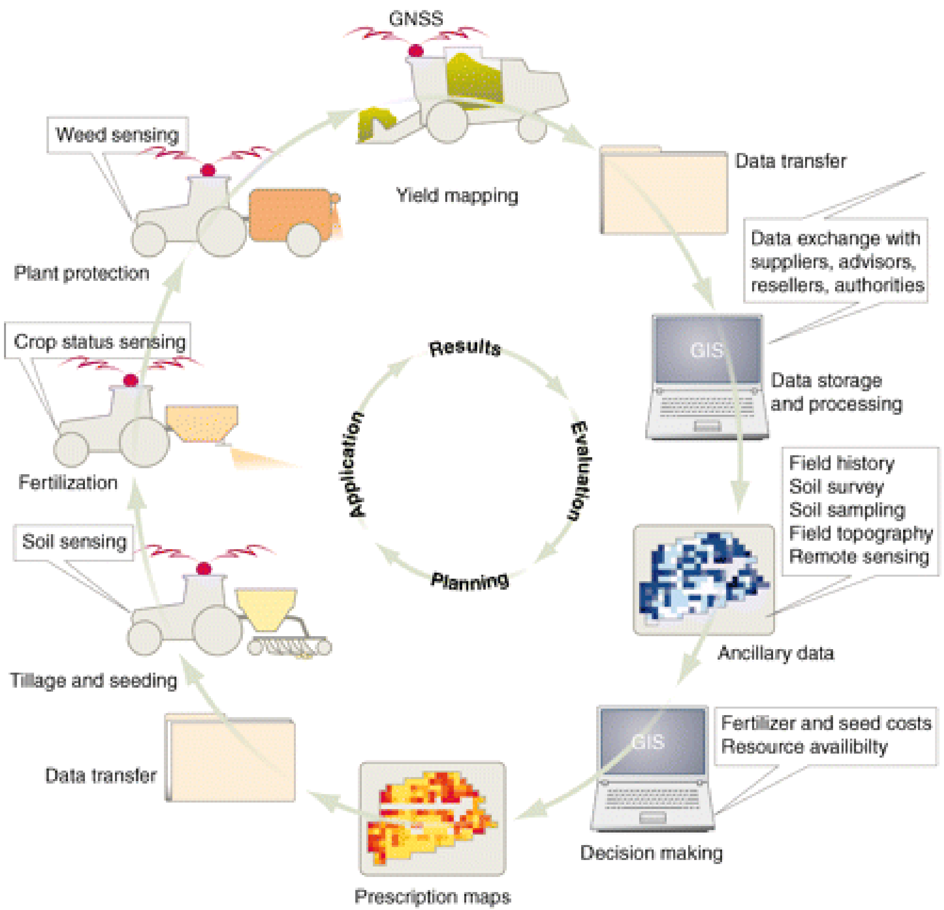
http://www.cema-agri.org/

What is Precision Agriculture?

Precision Agriculture is a management strategy that gathers, processes and analyzes temporal, spatial and individual data and combines it with other information to support management decisions according to estimated variability for improved resource use efficiency, productivity, quality, profitability and sustainability of agricultural production

ISPA

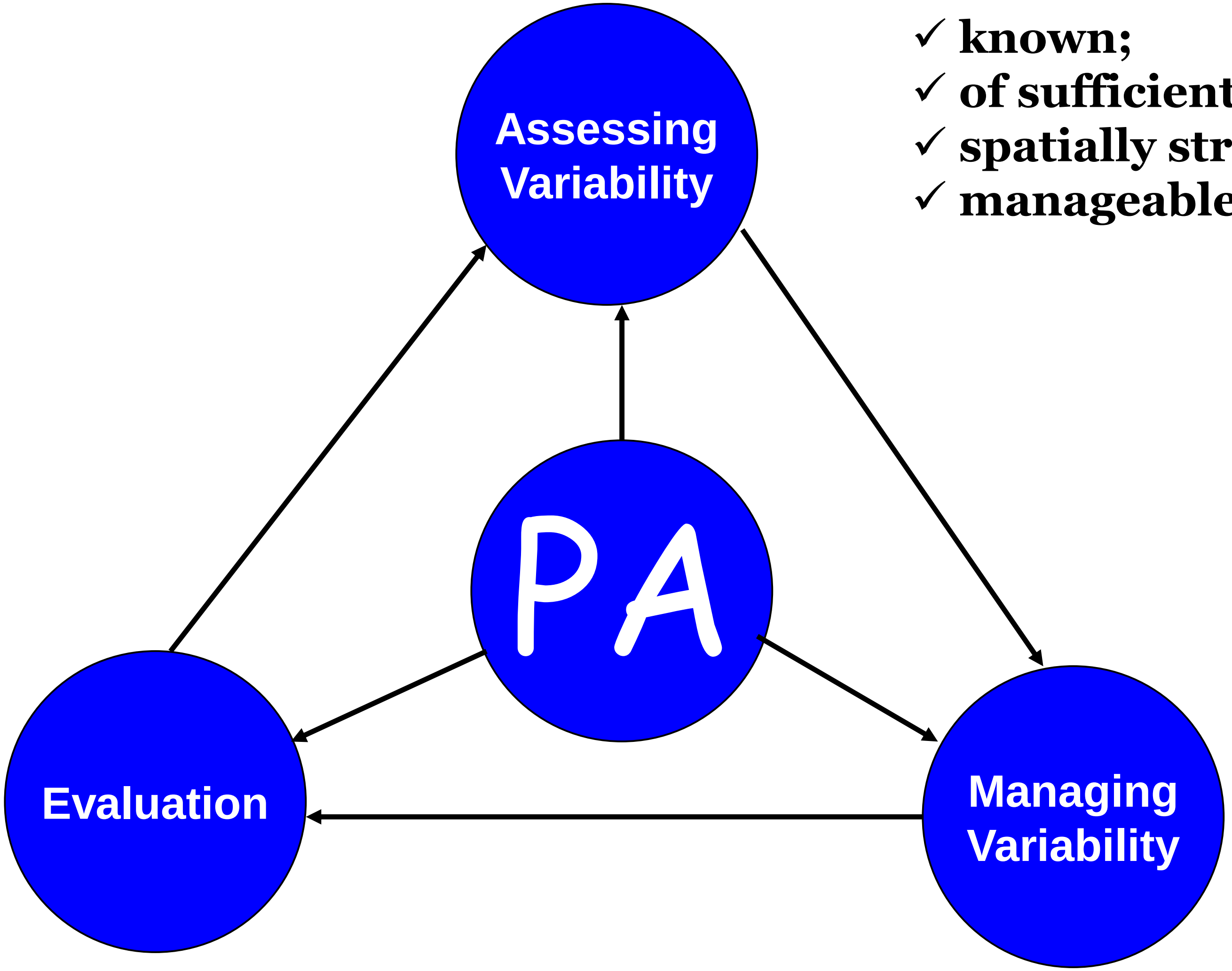
Precision Agriculture



Spatial and temporal optimization of key factors influencing crop yield, profitability and environmental footprint

Gebbers and Adamchuk. 2010. Science

Steps of Precision Agriculture



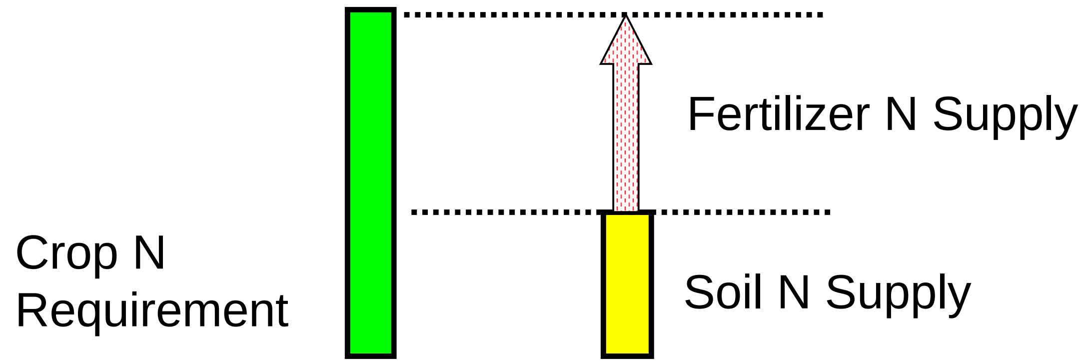
- ✓ known;
- ✓ of sufficient magnitude;
- ✓ spatially structured (not random);
- ✓ manageable.

(Pierce and Nowak, 1999. Advances in Agronomy)

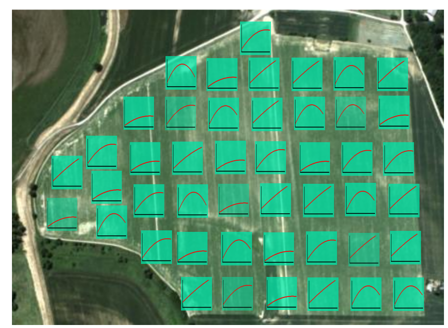
Precision Nitrogen Management

Matching N supply with crop N requirement in:

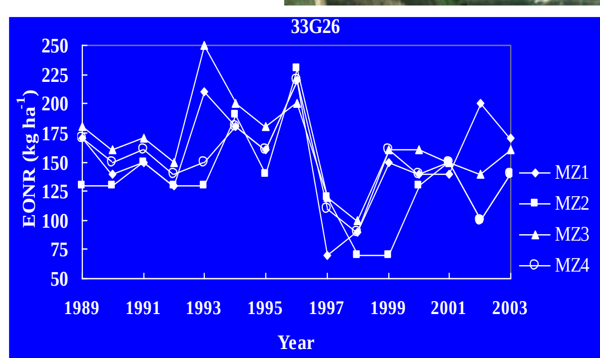
Total Rate:

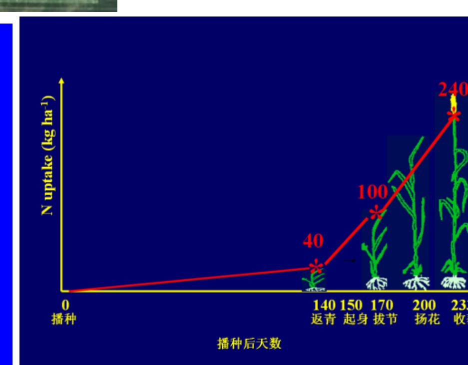


Space:



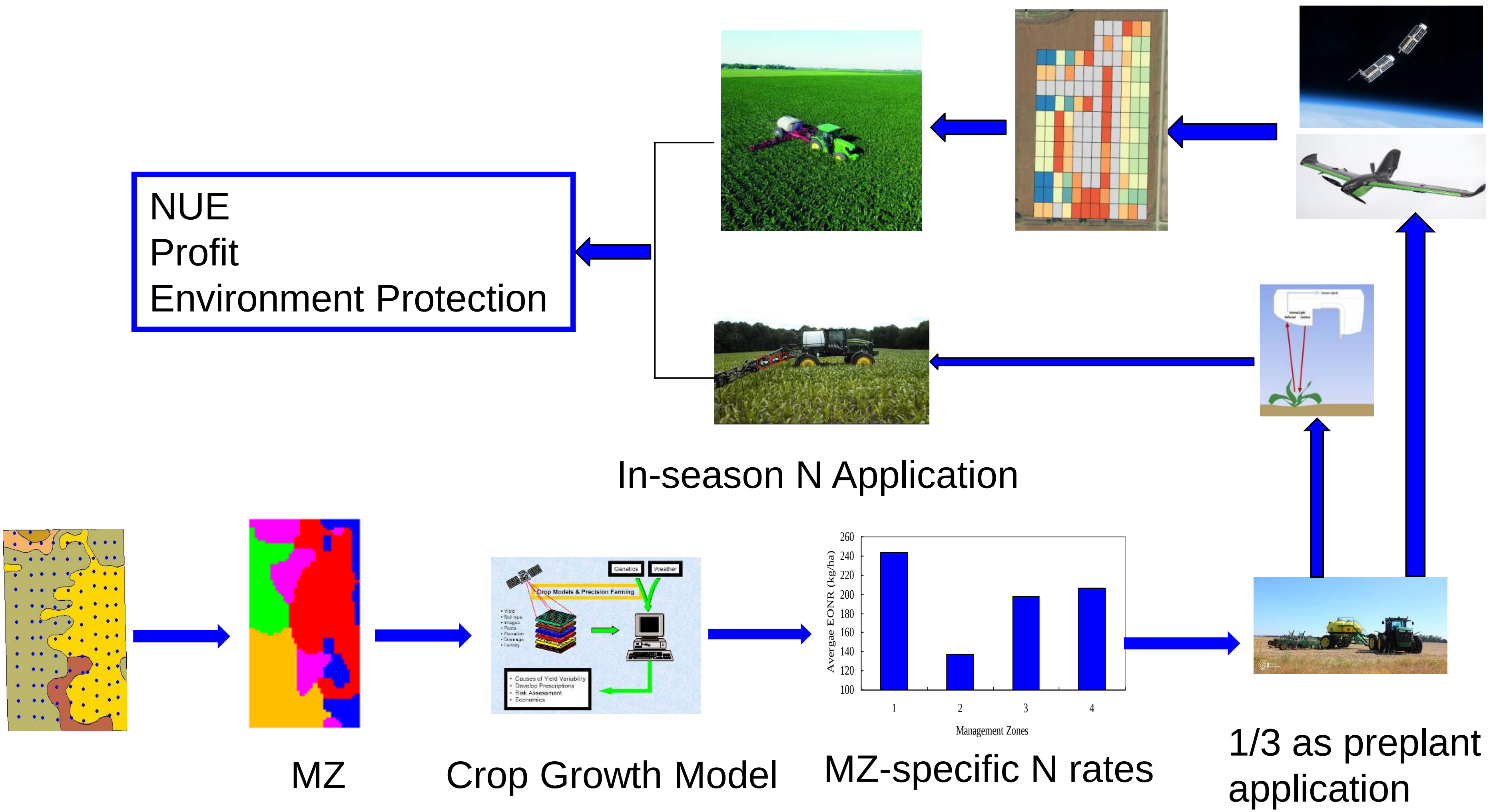
Time:





How are you managing N?

An Integrated Precision Nitrogen Management Strategy



What is Management Zone?

Management zones: subregions of a field with unique yet relatively homogeneous soil or landscape conditions and similar yield limiting factors that can be managed uniformly with a single rate of crop input or single set of management practices (Mulla et al., 1993; Doerge, 1999).

A way of classifying the spatial variability within a field

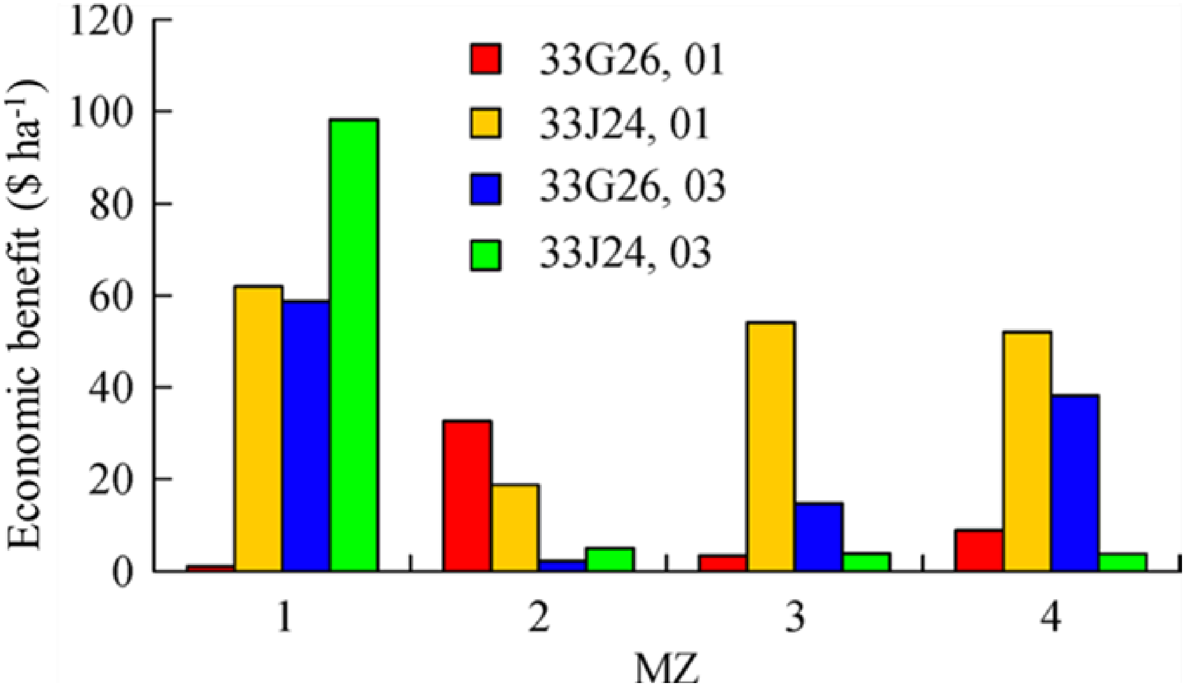
Zone-based Precision N Management is Profitable

Studies in Colorado (Delgado et al., 2005; Koch et al., 2004):

Reduced 25% nitrate-N leaching losses;

Reduced 6-46% N fertilizers;

Increased 18-30 $ ha^{-1} profits



Miao et al., 2018

Management Zone Delineation

To be successful, the delineation strategy must be based on:

True cause and effect relationships between site characteristics and crop yield.

Doerge, 1999.

What are the Practical Considerations for Defining Management Zones?

Relationship with crop yield:

Direct effect on crop yield

Cost of the data:

Free or low cost data:

Grower's local knowledge

Soil survey maps

DEM data and terrain attributes

Remote sensing images

Yield maps

LiDAR data

Doerge, 1999.

What are the Practical Considerations for Defining Management Zones

Data that are quantitative and repeatable:

Topography (DEM)

EC

Soil color （or brightness）

Some soil physical properties

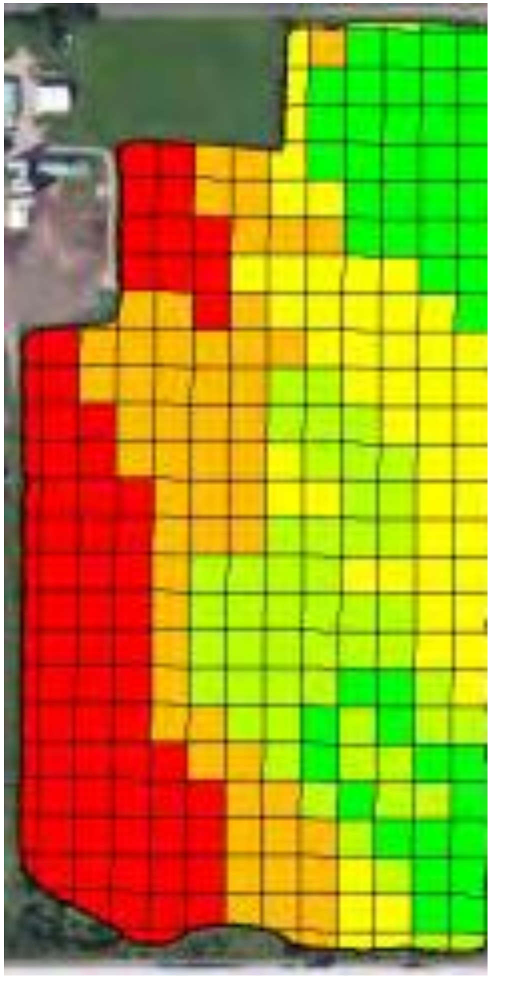
Density of the data:

Yield maps

DEM

EC and other proximal sensor-based data

Remote sensing data



Doerge, 1999.

What variables are you using in your management zone delineation approaches?

Three Basic Approaches to Management Zone Delineation

Soil and/or landscape variables

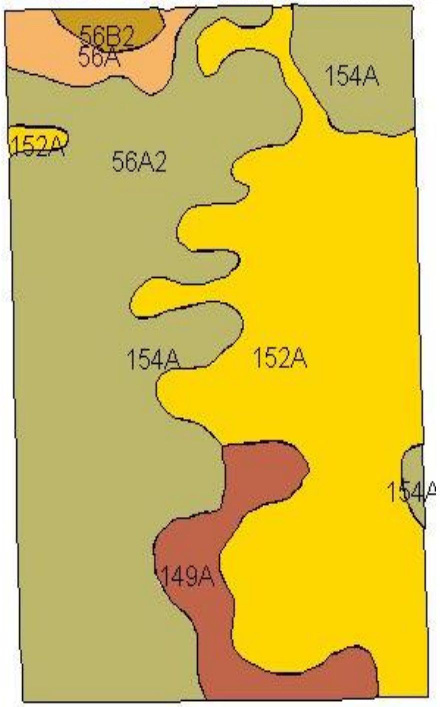
Soil survey maps;
Soil sampling data;
Soil electrical conductivity (EC);
Soil organic matter estimated using proximal or remote sensing;
Bare soil images or soil brightness;
Cation exchange capacity;
Soil texture;
Landscape properties or terrain attributes;
…

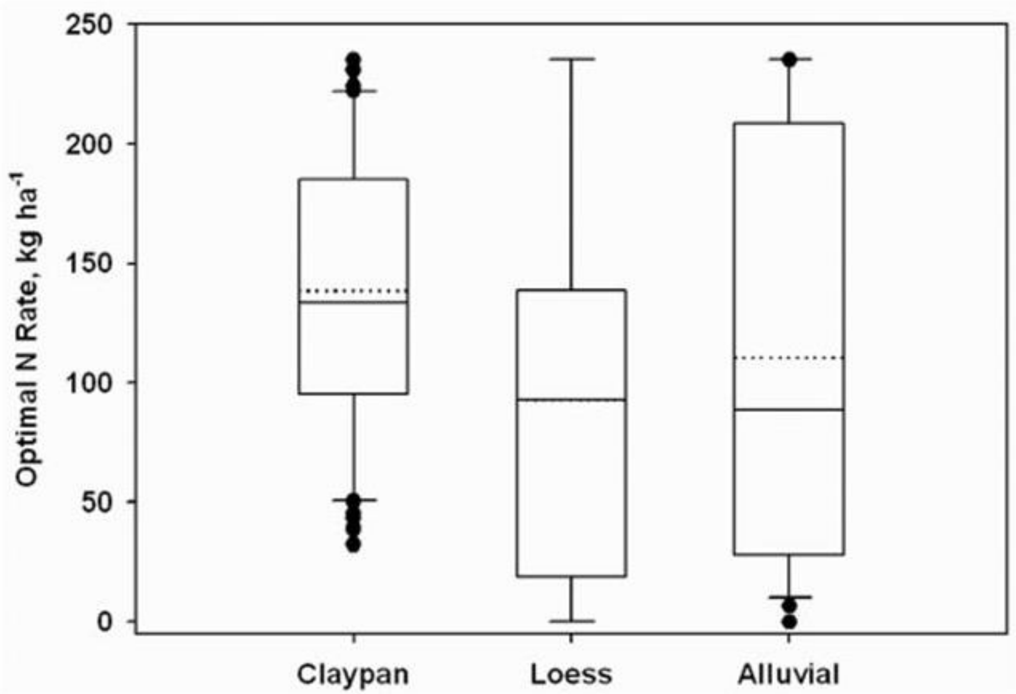
Yield maps and remote sensing images

Integrated approaches combing soil-landscape factors and yield/remote sensing images

1. Soil and/or Landscape Factors

1). Traditional Soil Survey





Roberts, et al., 2010. Agronomy Journal

Limitation of Soil Survey Maps

Based on soil genesis;

Not necessarily result in yield differences;

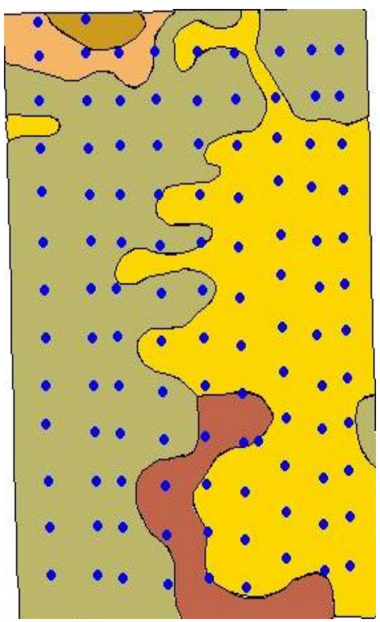
Not necessarily require different input rates;

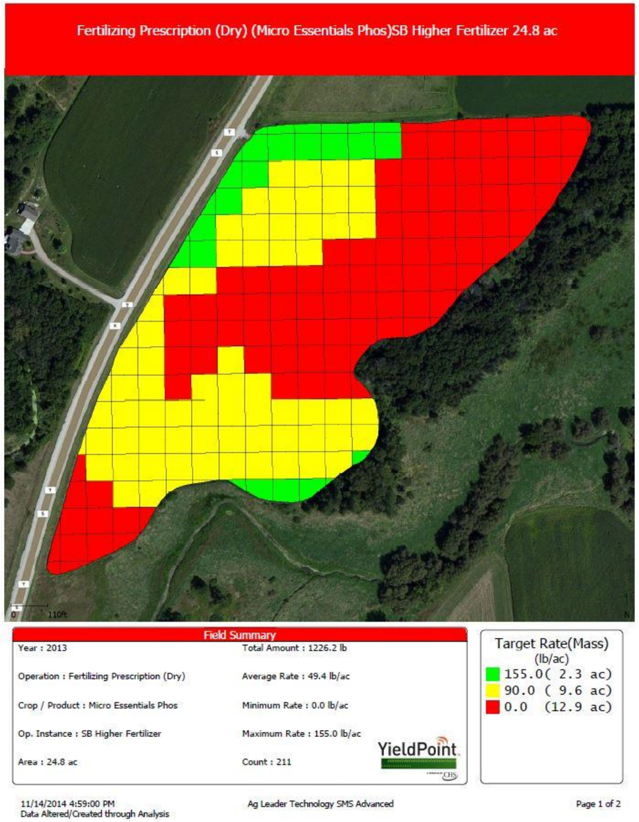
Ignore internal variability;

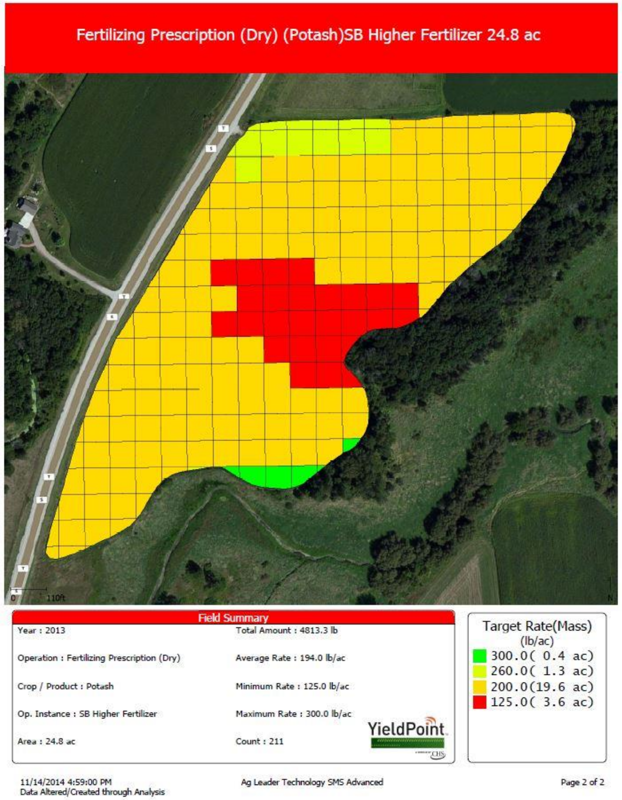
Coarse resolution;

1. Soil and/or Landscape Factors

2). Grid soil sampling

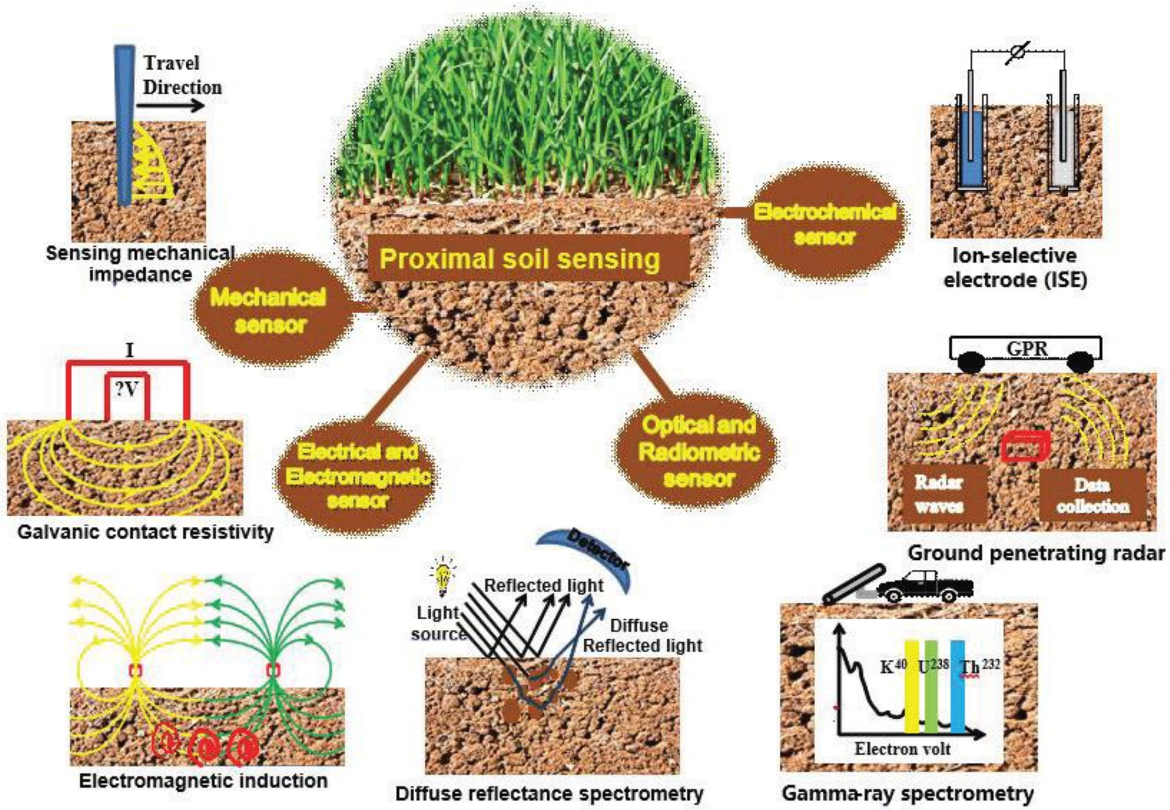






1. Soil and/or Landscape Factors

3) Proximal Soil Sensing and Mapping



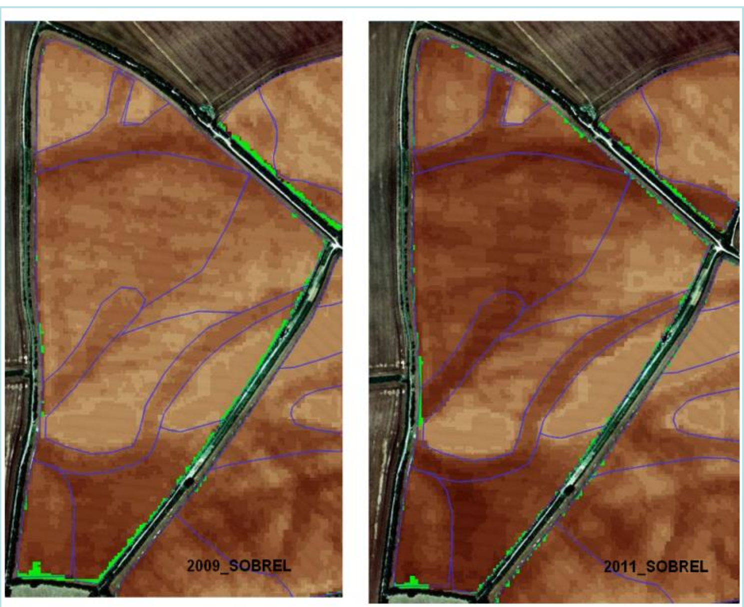
EC
OM
pH

（Adamchuk et al., 2018)

1. Soil-based Management Zones (Units)

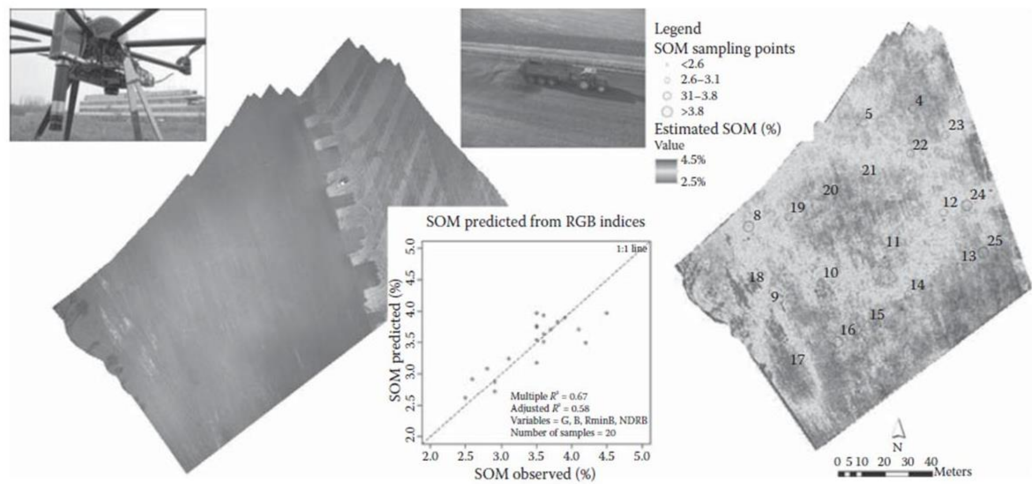
4) Remote Sensing-based Soil Mapping

Soil reflectance gives indication of soil texture, moisture, organic matter, etc.



Soil Brightness

(Gillingham, 2016)



UAV RS-based SOM Mapping

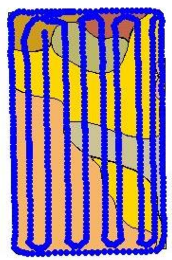
(Stoorvogel et al., 2015)

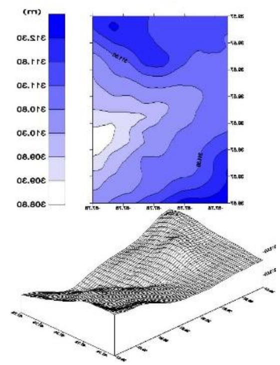
1. Soil and/or Landscape-based MZ

5). Topography and Terrain Attributes

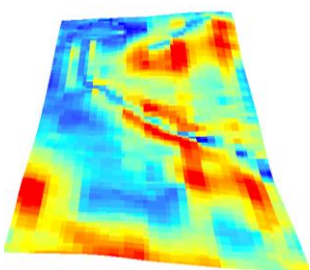
- **Topography**

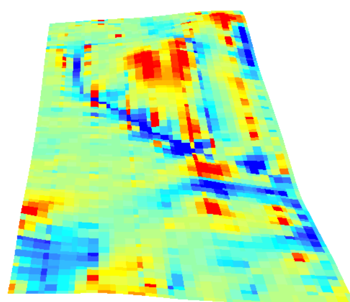
DGPS

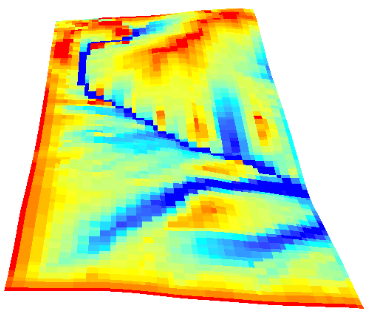


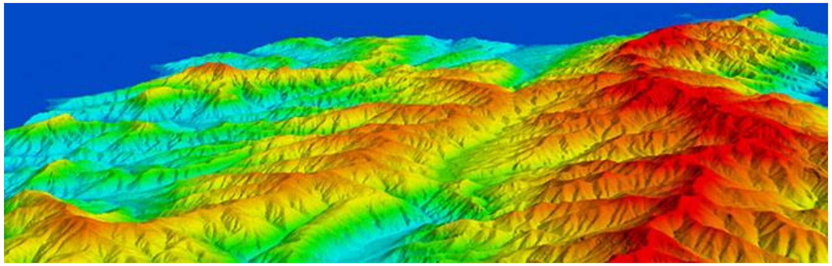


- Relative elevation
- Slope
- Aspect
- Curvature (plan, profile, tangential)
- SCA or flow accumulation
- Wetness index (or CTI)









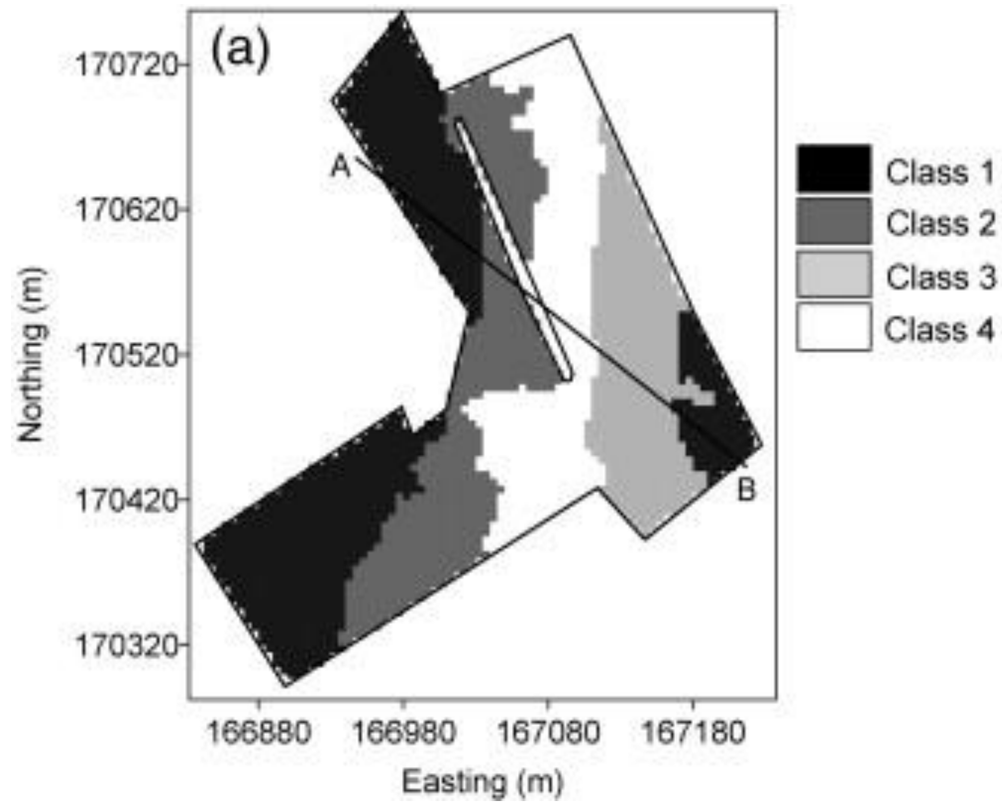
LIDAR data

1. Soil and/or Landscape-based MZ

6). Soil-landscape properties

Topographic attributes + EC

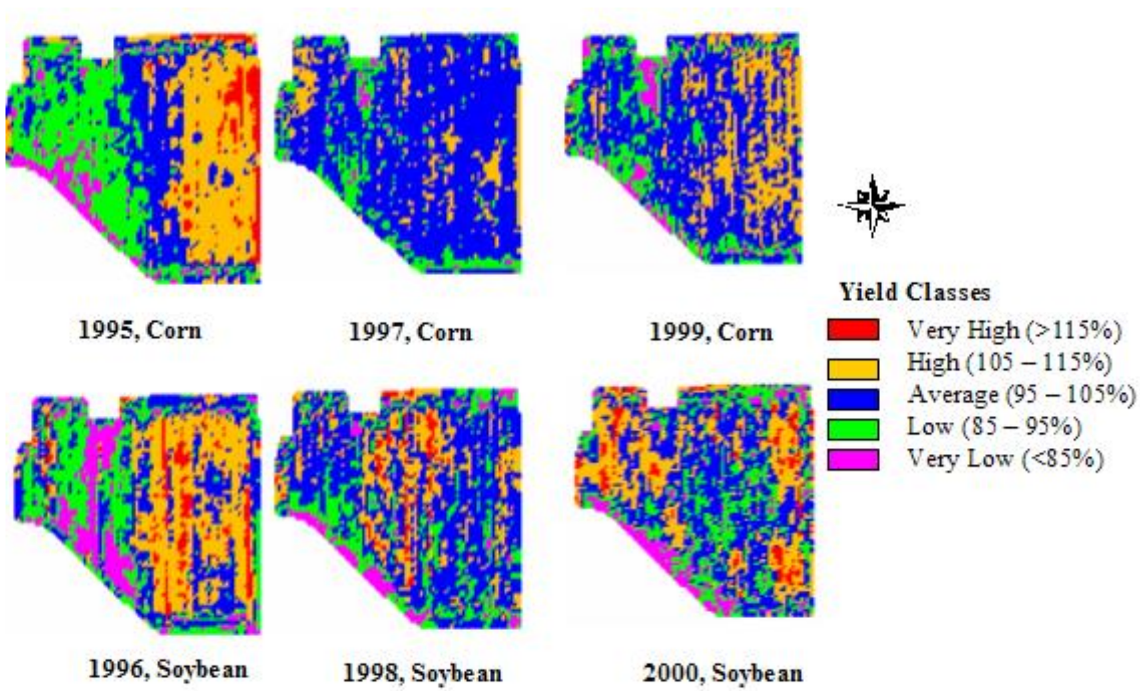
pH + EC + Elevation

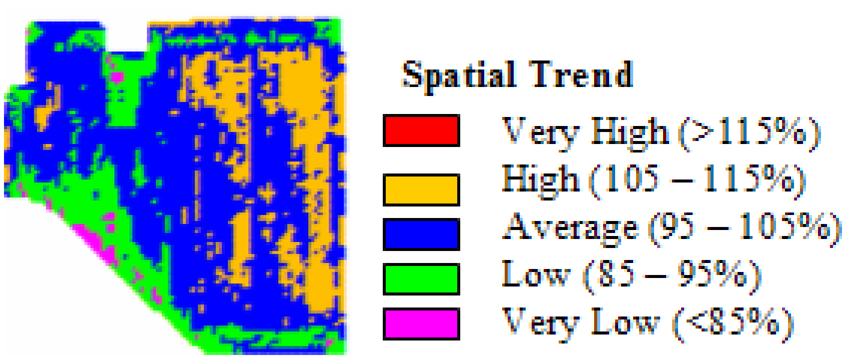


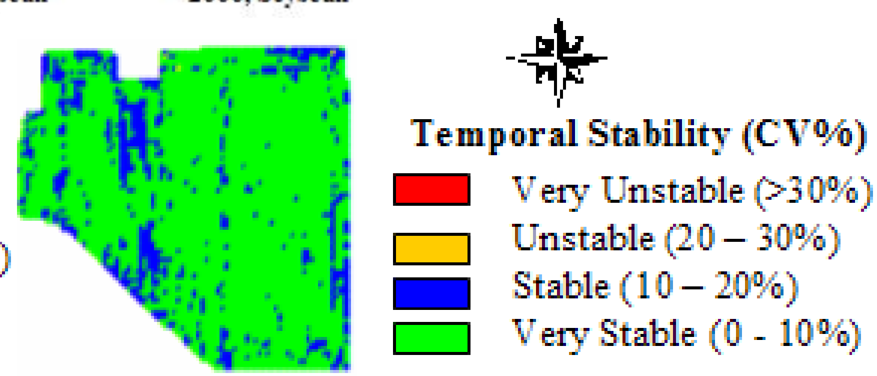
(Vitharana et al., 2008)

2. Crop-based MZ

1). Multi-year crop yield maps

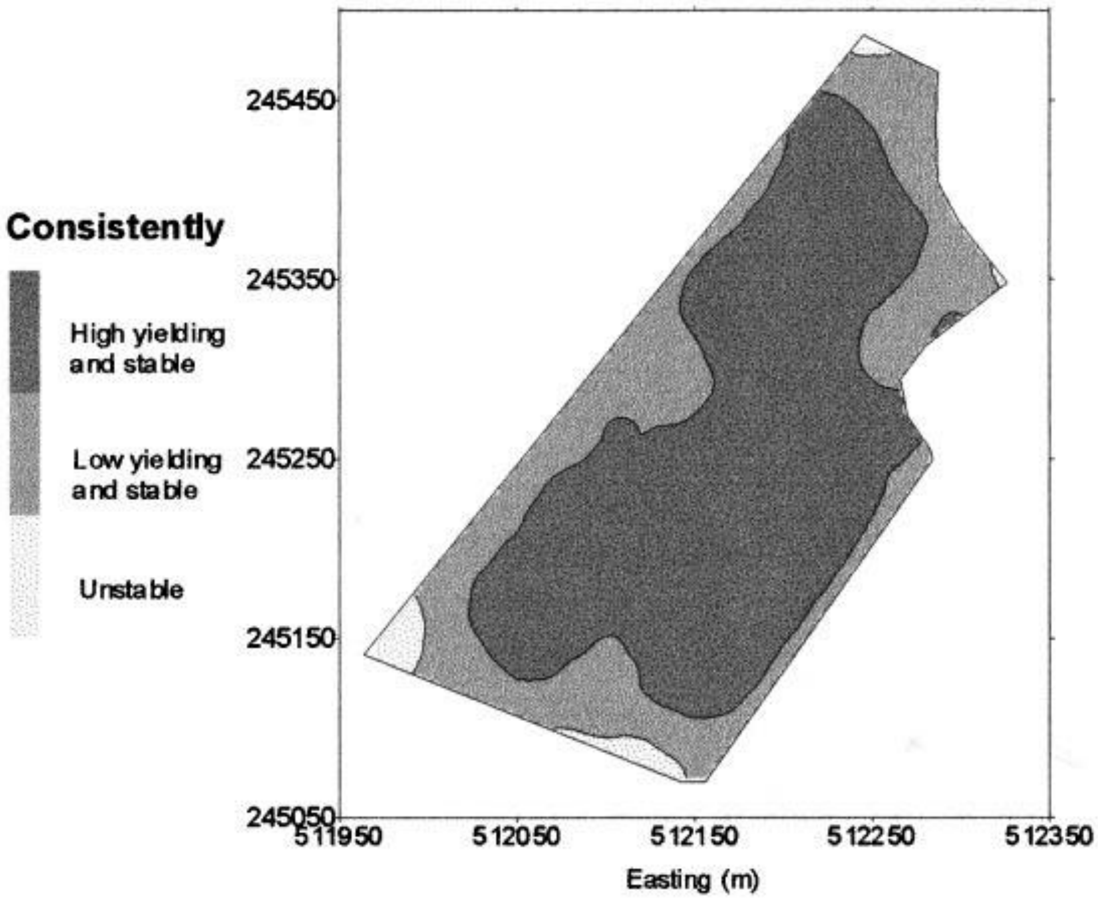






2. Crop-based MZ

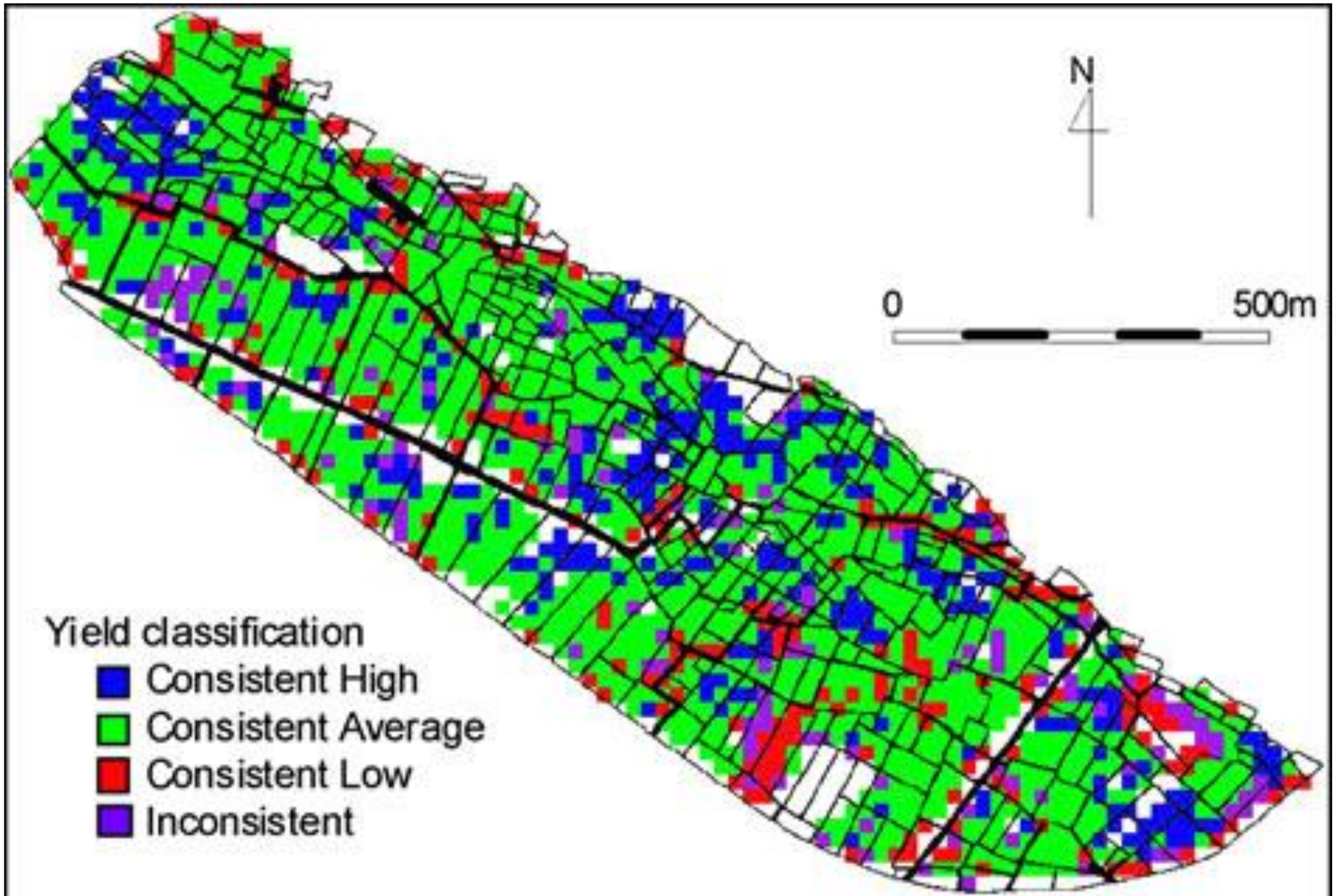
1). Multi-year crop yield maps



(Blackmore, S. 2000. Computers and Electronics in Agriculture)

2. Crop-based MZ

2). Multi-year remote sensing data



Wang et al., 2012.

3. Integrated Approaches (Soil-Landscape + Yield)

1). Yield + EC + Elevation

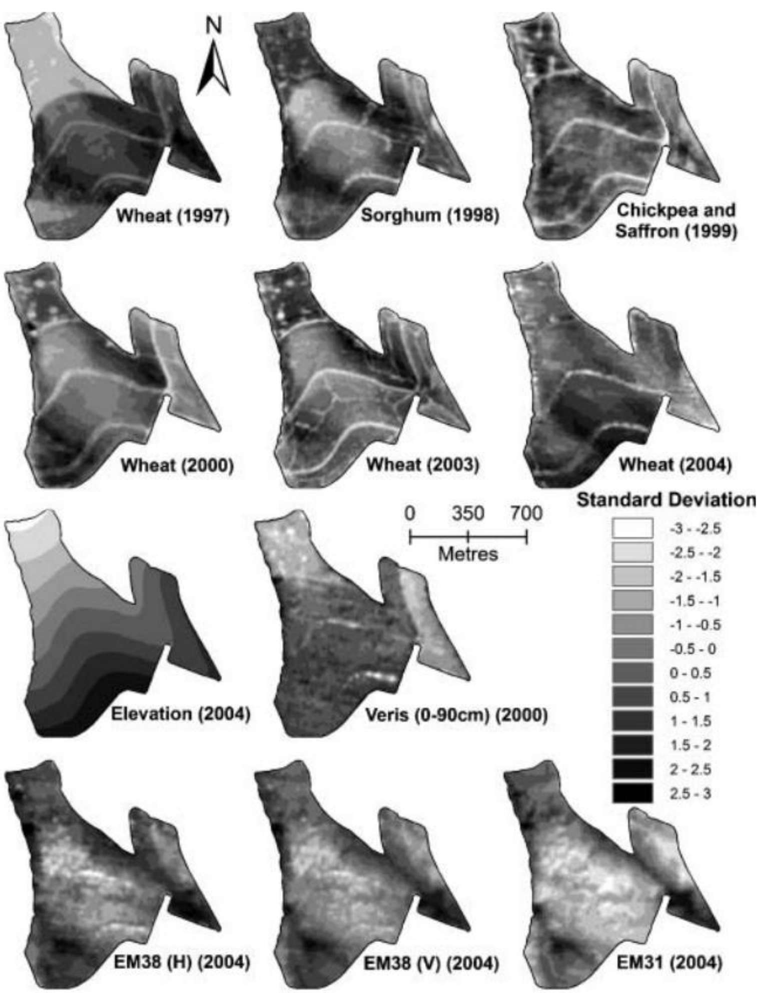


Fig. 5. Interpolated maps of all data layers available for analysis. Maps are presented using a common legend based on SDs.

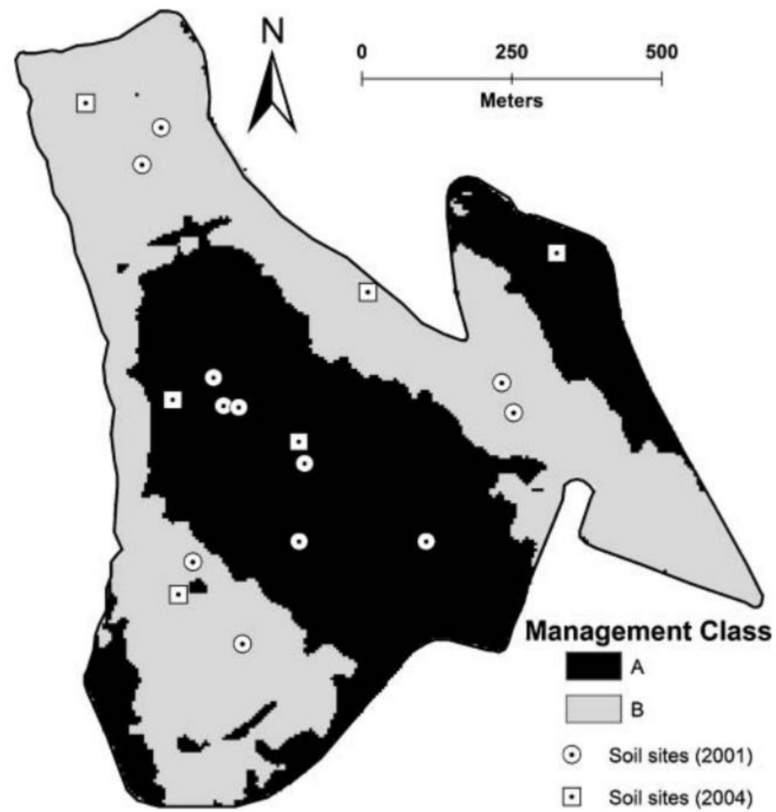


Fig. 7. The two management class map overlain with the stratified soil sample locations in 2001 and 2004.

Taylor et al., 2007.

3. Integrated Approaches (Soil Landscape + Yield)

2). Yield + Bare soil image + CEC+ OM+ Soil texture

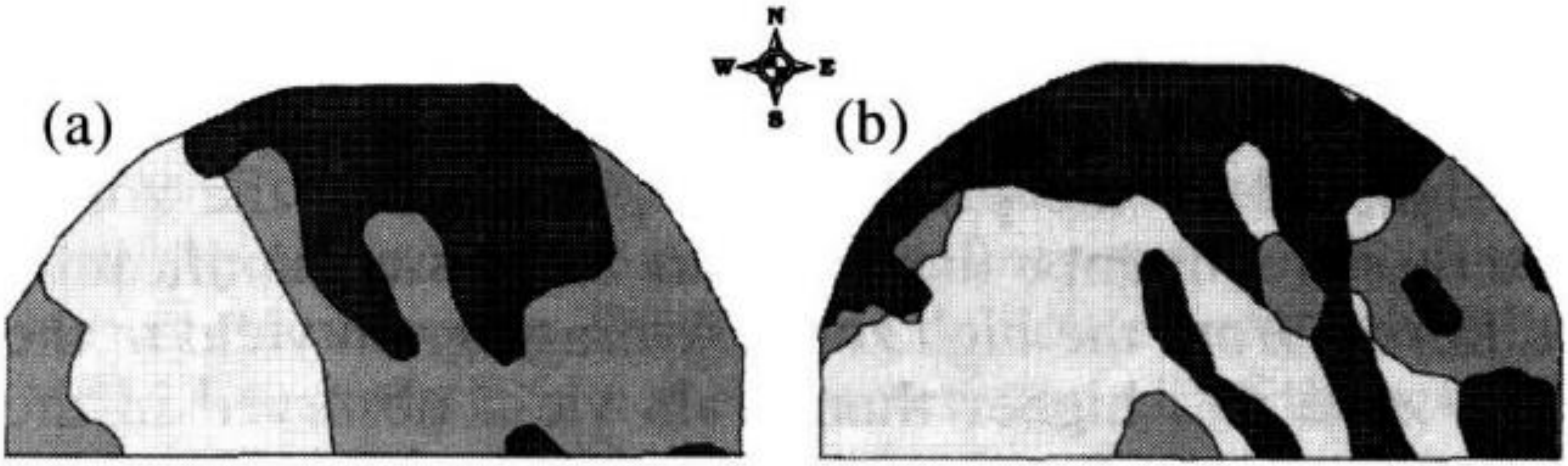
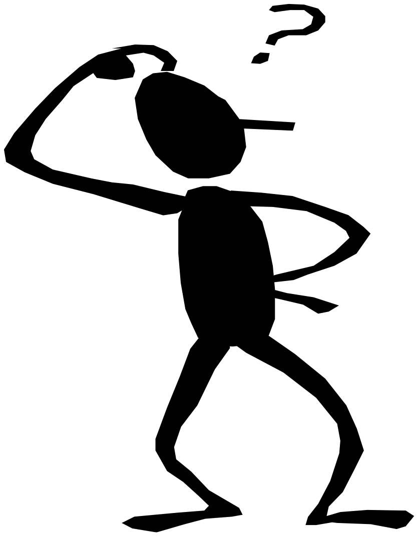
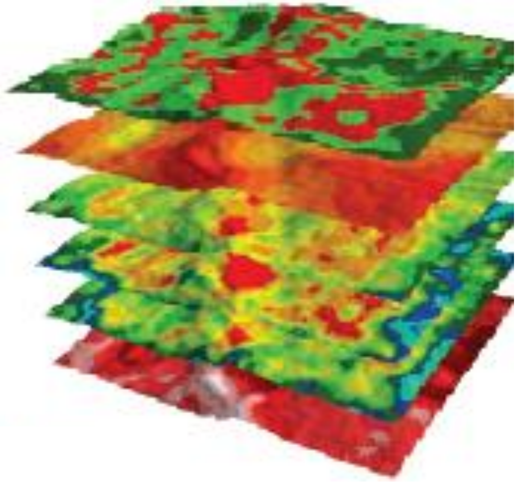


Fig. 1. (a) Soil-color-based management zone technique and (b) yield-based management zone technique for Site Year I. Low productivity = dark gray, medium productivity = light gray, high productivity = white.

Hornung et al., 2006.

How to determine the factors or variables for management zone delineation?





Key Factors Identification

Multivariate statistical analysis and machine learning for key factors identification

Artificial Neural Network Analysis

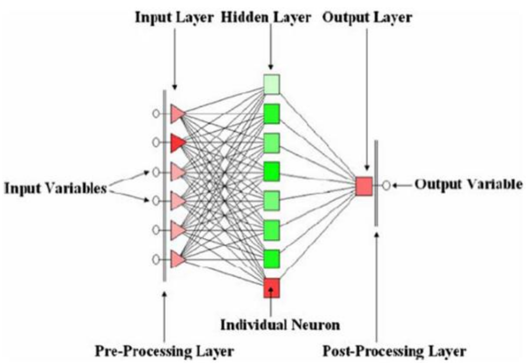


Fig. 1 Basic structure of a feed-forward multilayered perceptron (MLP) artificial neural network (adapted from StatSoft, 2002)

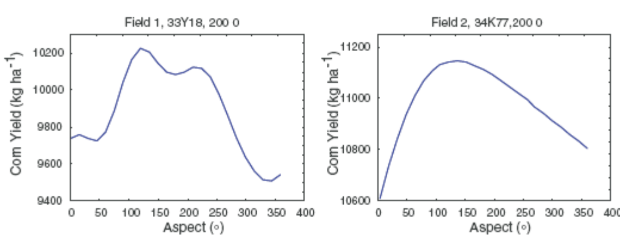


Fig. 10 Relationship between corn yield and aspect in Field 1 (33Y18, left) and 2 (34K77, right), 2000

Table 3 Ranking of important factors influencing corn yield and quality variability

Rank	Corn Yield				Corn Quality			
	1998	Ratio[a]	2000	Ratio	Protein	Ratio	Test wt.	Ratio
Field 1								
1	Aspect	2.05	Hybrid	2.15				
2	CEC	1.68	R_elev.	1.19				
3	R_elev.	1.49	CEC	1.16				
4	S	1.37	Aspect	1.15				
5	EC	1.35	Slope	1.07				
6	Zn	1.27	EC	1.07				
7	K	1.19	S	1.06				
8			pH	1.05				
9			K	1.05				
10			Zn	1.03				
11			CTI	1.02				
12			Tcurv.	1.00				
R^{2b}		0.68		0.80				
Field 2								
1	Aspect	1.68	S	2.23				
2	R_elev.	1.42	R_elev.	2.00				
3	EC	1.38	CEC	1.84				
4	Slope	1.35	pH	1.70				
5	pH	1.31	Zn	1.49				
6	CEC	1.27	EC	1.43				
7	P	1.19	Hybrid	1.43	pH	4.35	Slope	1.91
8	Zn	1.17	Aspect	1.42	EC	4.28	S	1.83
9	S	1.10	Slope	1.31			pH	1.82
10	Pcurv.[c]	1.05	P	1.25			P	1.79
11	Tcurv.[d]	1.05	CTI	1.12			CTI	1.29
12			Tcurv.	1.04			Tcurv.	1.07
13			Pcurv.	1.03			Pcurv.	1.05
R^2		0.68		0.83		0.99		0.99

[a]Sensitivity ratio

[b]Coefficient of determination for the whole dataset

[c,d]Profile and tangential curvature

Aspect

EC

Relative Elevation

CEC

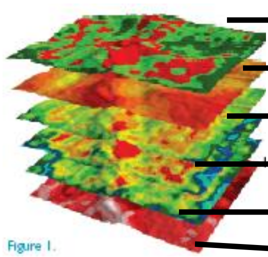
Zn

S

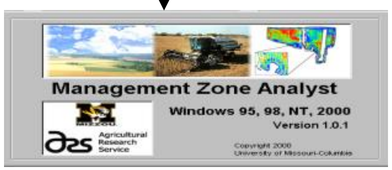
Miao et al., 2006, Precision Agriculture

An Integrated Approach to MZ Delineation

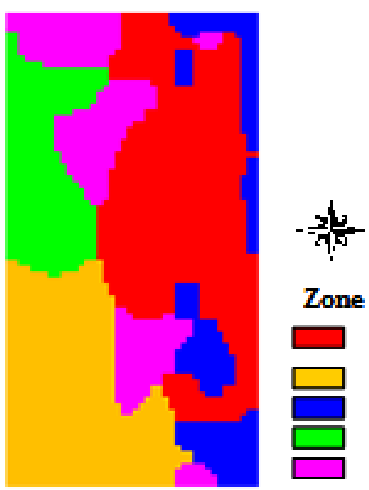
Relative elevation + OM + Slope + EC + Yield



Relative Elevation
Organic Matter
Slope
Electrical Conductivity
Yield **S**patial **T**rend Map
Yield **T**emporal **S**tability Map



MZ Analysis



ROSE_YSTTS


Front. Agr. Sci. Eng.
https://doi.org/10.15302/J-FASE-2018230
Available online at http://journal.hep.com.cn/fase

RESEARCH ARTICLE

An integrated approach to site-specific management zone delineation

Yuxin MIAO (✉), David J. MULLA, Pierre C. ROBERT

Precision Agriculture Center, Department of Soil, Water and Climate, University of Minnesota, St. Paul, MN 55108, USA

Miao et al., 2018

What are the Criteria for Evaluating Delineated Management Zones

- The ability to group areas with similar soil test results into the same zone (soil nutrient variability minimization);

- The ability to group areas with similar yields into the same zone(yield variability minimization); and

- The ability to improve fertilizer recommendations (fertilizer recommendation error minimization).

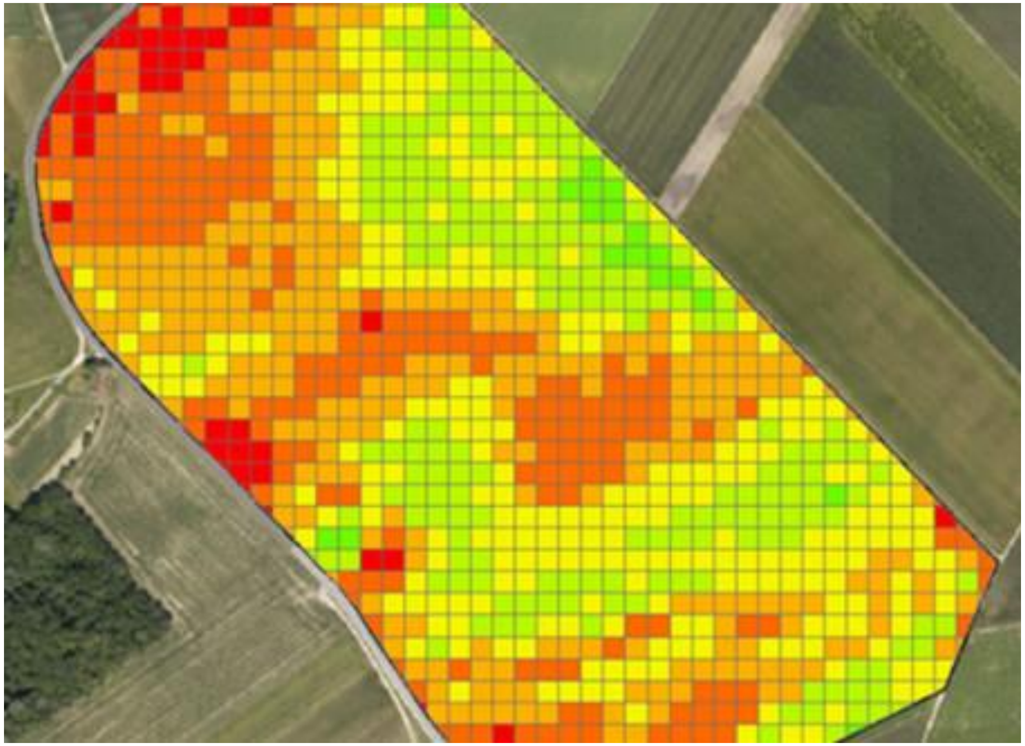
- Increase profitability or resource use efficiency (benefit optimization).

Chang et al., 2004; Hornung et al., 2006.

How to Evaluate a Management Zone Strategy?

Historical:

Yield and income



Yield or profitability difference map

Doerge, 1999.

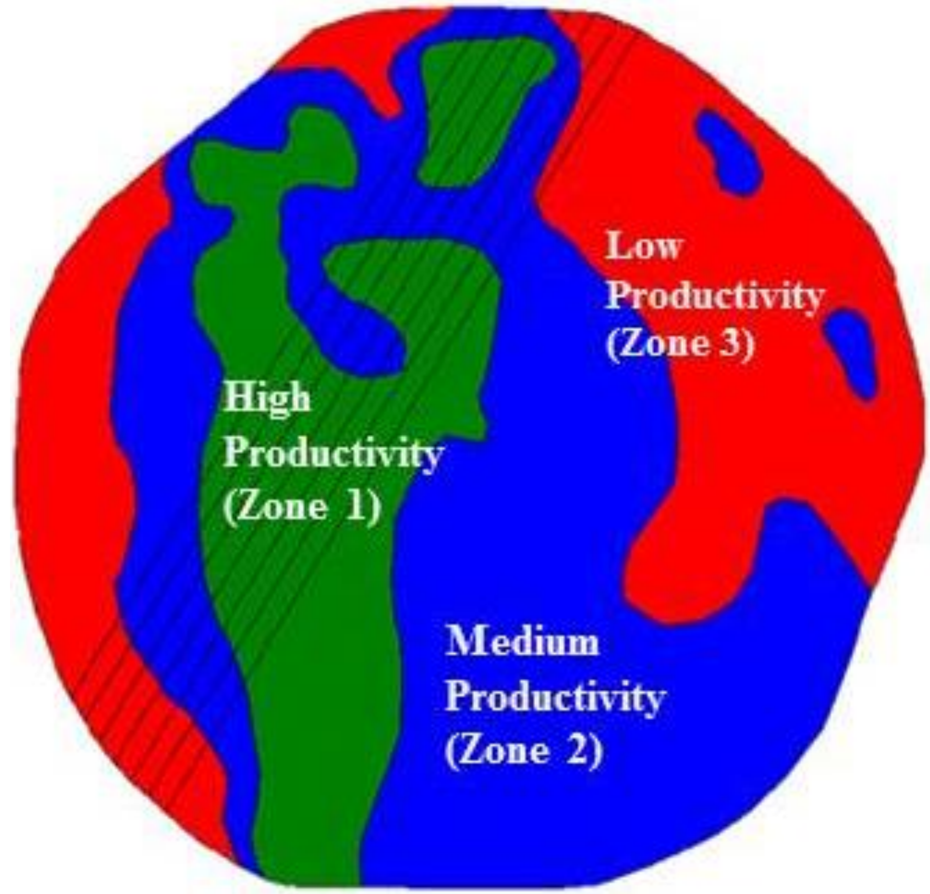
How to Evaluate a Management Zone Strategy?

Direct:

Side-by-side comparison

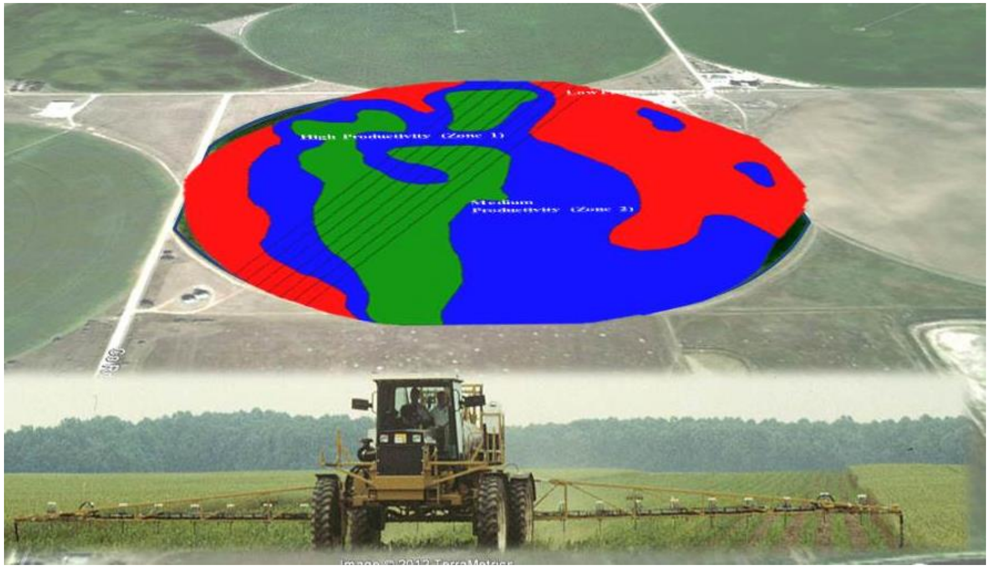
Quantitative, spatially robust, and requires no specialized equipment beyond a yield monitoring and mapping system.

Limited risk



Doerge, 1999.

How to determine suitable N rates in different MZs?



High yield zone?

Normal yield zone?

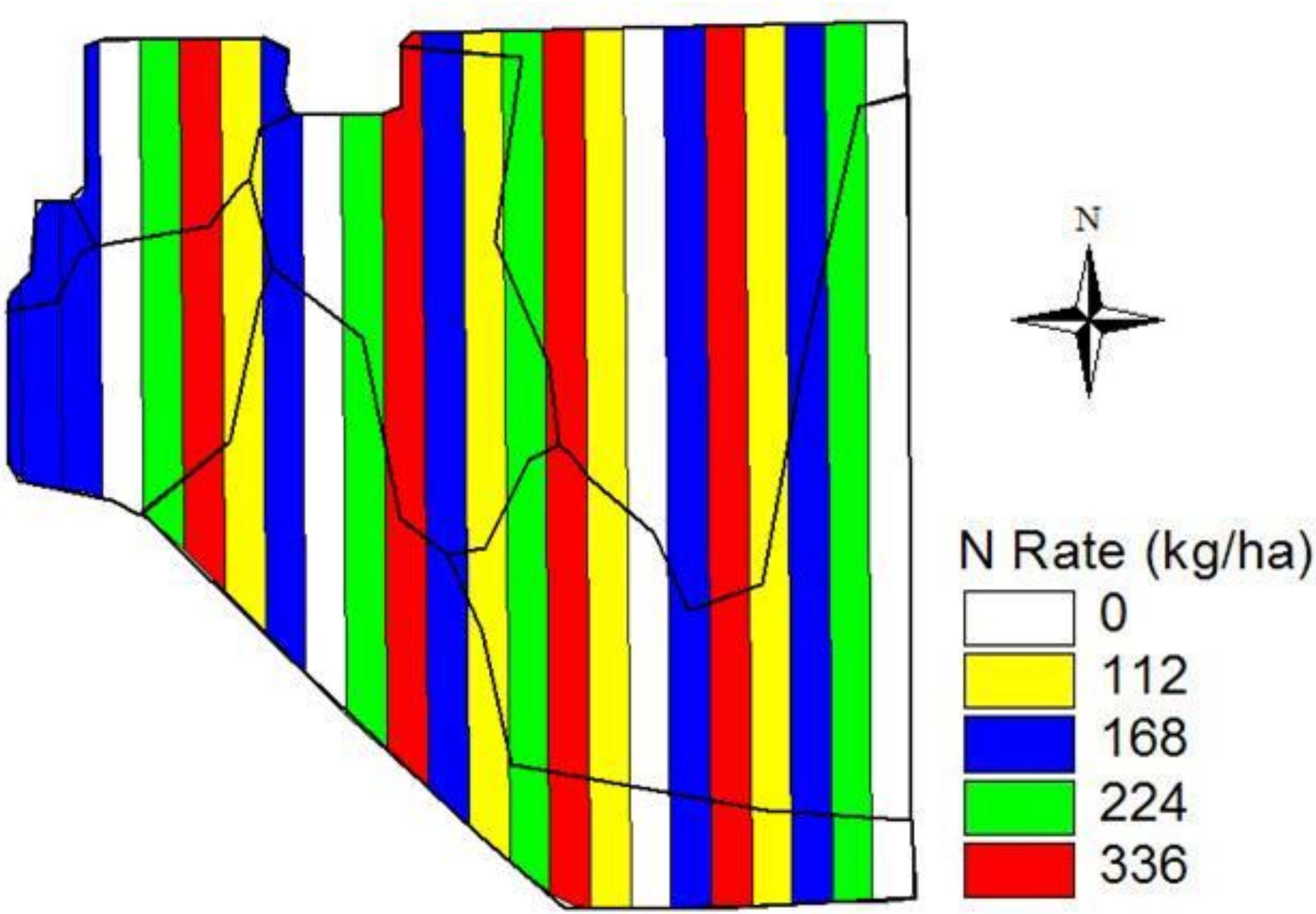
Low yield zone?

Diagnosis of yield limiting factors

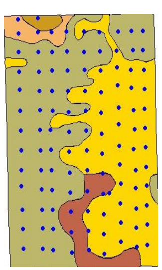
Unstable?

Need dynamic decision making

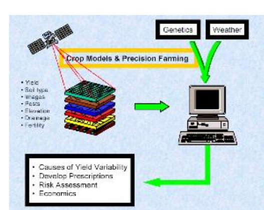
Nitrogen Strip Trials



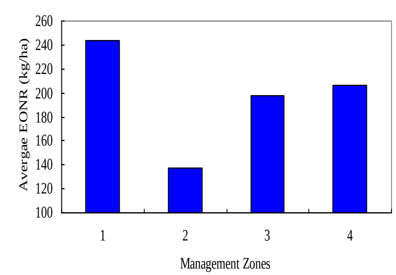
An Integrated Precision Nitrogen Management Strategy



MZ

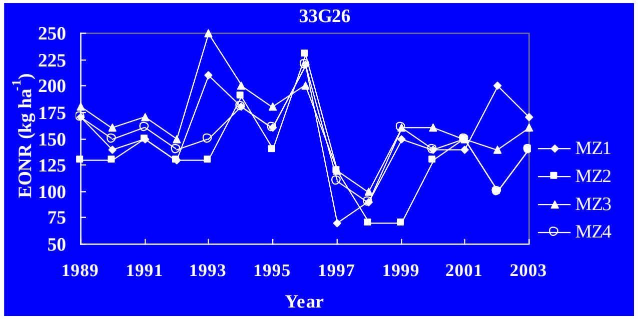


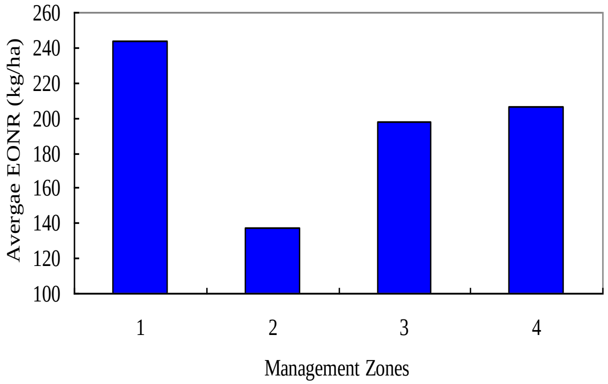
Crop Growth Model

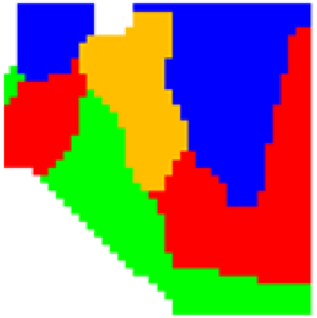


MZ-specific N rates

Crop Growth Model-based Zone-Specific N Management



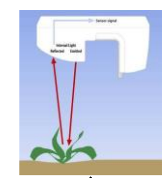


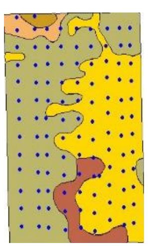


Zone- & Hybrid-specific N Application

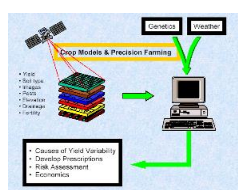
Miao et al., 2006. Agronomy Journal

An Integrated Precision Nitrogen Management Strategy

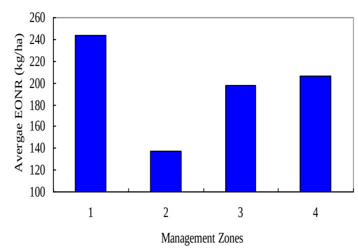




MZ



Crop Growth Model



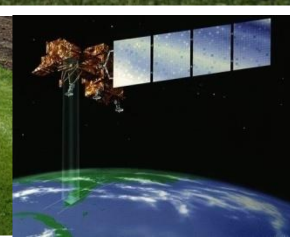
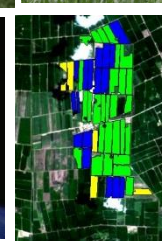
MZ-specific N rates

1/3 as preplant application

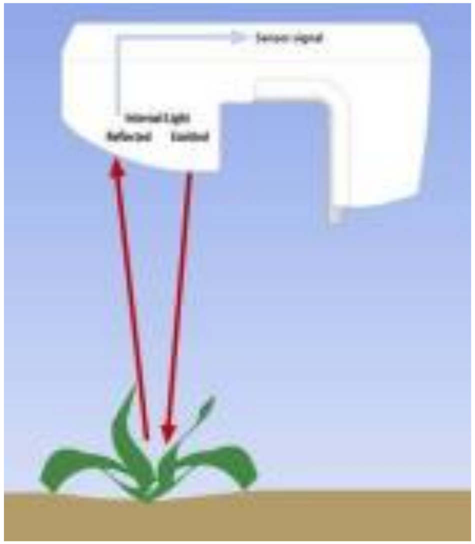
What are the Proximal or Remote Sensing Technologies you are using?

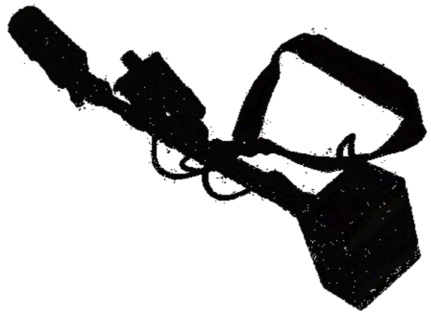




Active Canopy Sensor: GreenSeeker





R: 650$\pm$10nm
NIR: 770$\pm$15nm

NDVI=(NIR-R)/(NIR+R)

RVI=NIR/R

Other Two Band Active Canopy Sensors

Crop Circle ACS 210

590$\underline{+}$5.5, 880$\underline{+}$10

Three Band Active Canopy Sensors

Crop Circle ACS-430

670nm, 730nm and 780 nm

Height independent spectral reflectance measurements.

(0.25 m to 2.0 m)

RapidSCAN CS-45

670nm, 730nm and 780 nm

0.8 kg

Integrates a data logger, graphical display, GPS, crop sensor and power source into one, small compact instrument.

Height independent spectral reflectance measurements.

(0.3 m to 3 m)

User Configurable Active Canopy Sensors

Active Canopy Sensor Crop Circle ACS 470

450 ± 20nm, 550 ± 20nm, 650 ± 20nm,
670 ± 11nm, 730 ± 10nm, 760LWP (interference filters)

- ACS 470 active canopy sensor, user configurable
- Choice of 6 possible wave bands
- Red edge and green bands more sensitive to plant N status than red band

Active Canopy Sensor-based Precision N Management Strategy (NFOA Algorithm)

Estimated Optimum N Rate

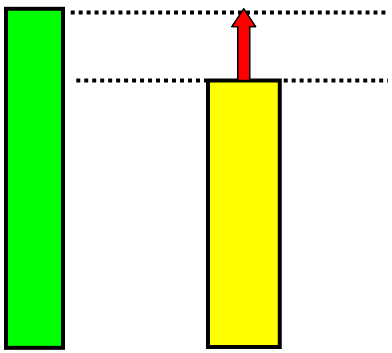
Early Season N Application

(1/3 as preplant application)

In-season Adjustment

Sidedressing N Rate

Grain yield

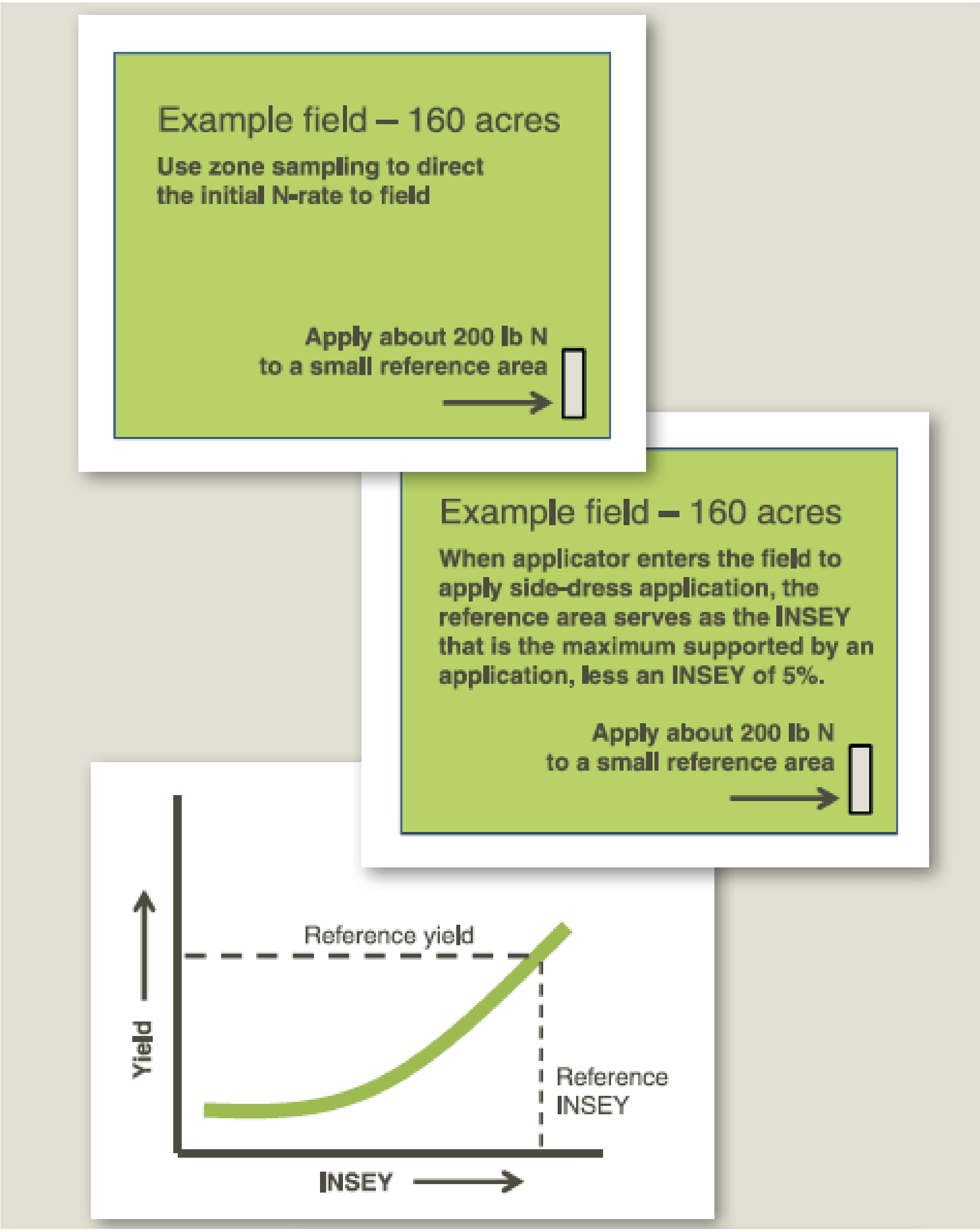


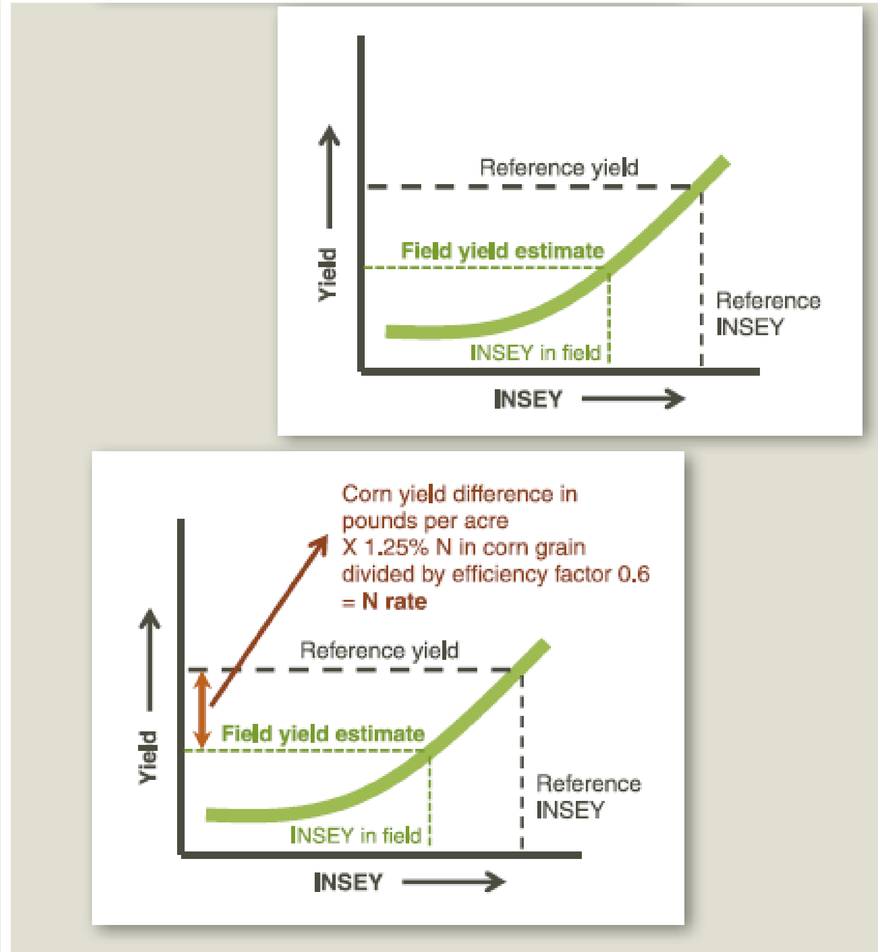
Yield Response to Sidedressing N

Yield Potential with sufficient N (YP_N)

Yield Potential without sidedressing N (YP_N)

NDSU & NFOA





Franzen et al., 2014

Algorithm inputs for GreenSeeker and Holland Scientific Crop Circle sensors in North Dakota corn yield prediction and for directing N rates for side-dress N application.

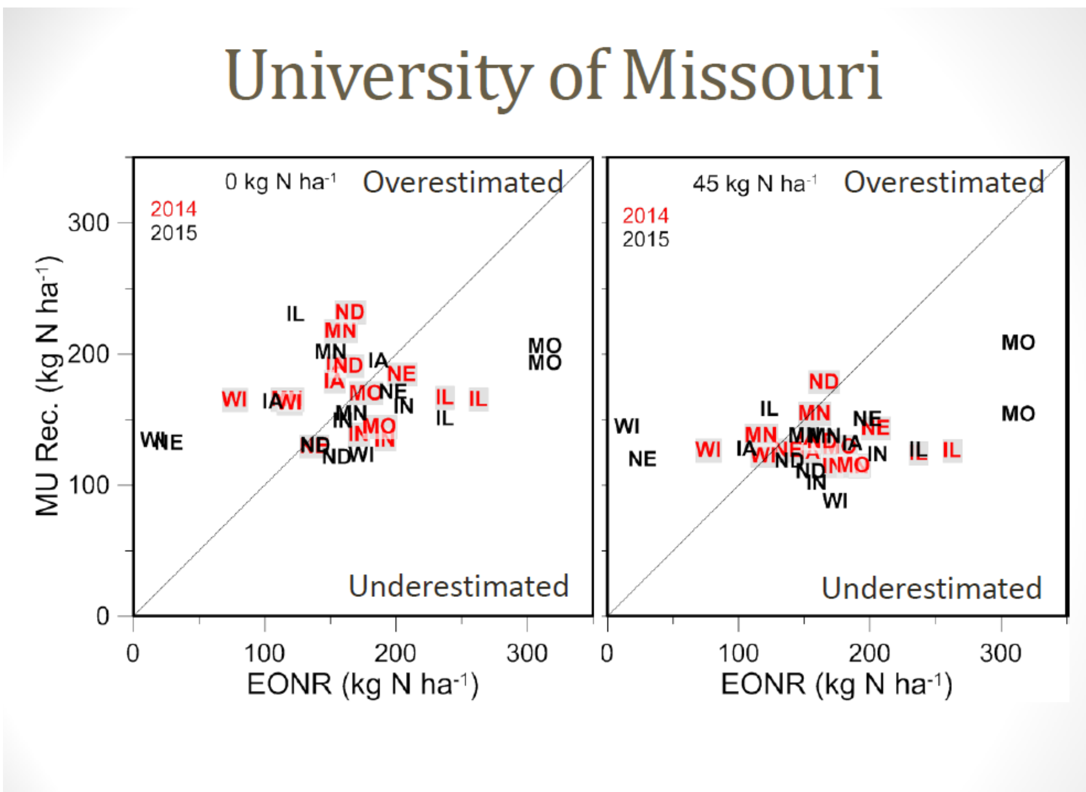
Sensor	Wavelength for NDVI	Growth Stage	Basic Yield Prediction Formula	Minimum INSEY for N rate
West River No-till				
GreenSeeker	Red	V6	Yield = (188094 X INSEY) + 29	0.0001
GreenSeeker	Red Edge	V6	Yield = (325010 X INSEY) + 46	0.00003
Crop Circle	Red	V6	Yield = (229555 X INSEY) + 41	0.0001
Crop Circle	Red Edge	V6	Yield = (399336 X INSEY) + 60	0.00003
GreenSeeker	Red	V12	Yield = (71686 X INSEY) + 57	0.0002
GreenSeeker	Red Edge	V12	Yield = (139218 X INSEY) + 50	0.00015
Crop Circle	Red	V12	Yield = (120175 X INSEY) + 35	0.0002
Crop Circle	Red Edge	V12	Yield = (277715 X INSEY) + 11	0.00015
High-clay Soils Eastern North Dakota				
GreenSeeker	Red	V6	Yield = (85506 X INSEY) + 110	0.0002
GreenSeeker	Red Edge	V6	Yield = (146652 X INSEY) + 93	0.00015
Crop Circle	Red	V6	Yield = (94286 X INSEY) + 120	0.0002
Crop Circle	Red Edge	V6	Yield = (161565 X INSEY) + 11	0.00015
GreenSeeker	Red	V12	Yield = (132082 X INSEY) + 62	0.0004
GreenSeeker	Red Edge	V12	Yield = (89991 X INSEY) + 91	0.0002
Crop Circle	Red	V12	Yield = (157411 X INSEY) + 48	0.0003
Crop Circle	Red Edge	V12	Yield = (274855 X INSEY) + 51	0.0002
Medium-texture Soils Eastern North Dakota				
GreenSeeker	Red	V6	Yield = (59103 X INSEY) + 128	0.0002
GreenSeeker	Red Edge	V6	Not established	
Crop Circle	Red	V6	Yield = (91892 X INSEY) + 133	0.0002
Crop Circle	Red Edge	V6	Yield = (55652 X INSEY) + 138	0.00006
GreenSeeker	Red	V12	Yield = (89116 X INSEY) + 99	0.0003
GreenSeeker	Red Edge	V12	Not established	
Crop Circle	Red	V12	Yield = (88306 X INSEY) + 109	0.0003
Crop Circle	Red Edge	V12	Yield = (196600 X INSEY) + 88	0.0002
Long-term No-till Eastern North Dakota				
GreenSeeker	Red	V6	Yield = (247906 X INSEY) + 67	0.00015
GreenSeeker	Red Edge	V6	Not established	
Crop Circle	Red	V6	Yield = (212021 X INSEY) + 103	0.00015
Crop Circle	Red Edge	V6	Not established	
GreenSeeker	Red	V12	Not established	
GreenSeeker	Red Edge	V12	Not established	
Crop Circle	Red	V12	Not established	
Crop Circle	Red Edge	V12	Yield = (363492 X INSEY) + 7	0.00015

Franzen et al., 2014

University of Missouri/USDA-ARS

Mizzou
University of Missouri

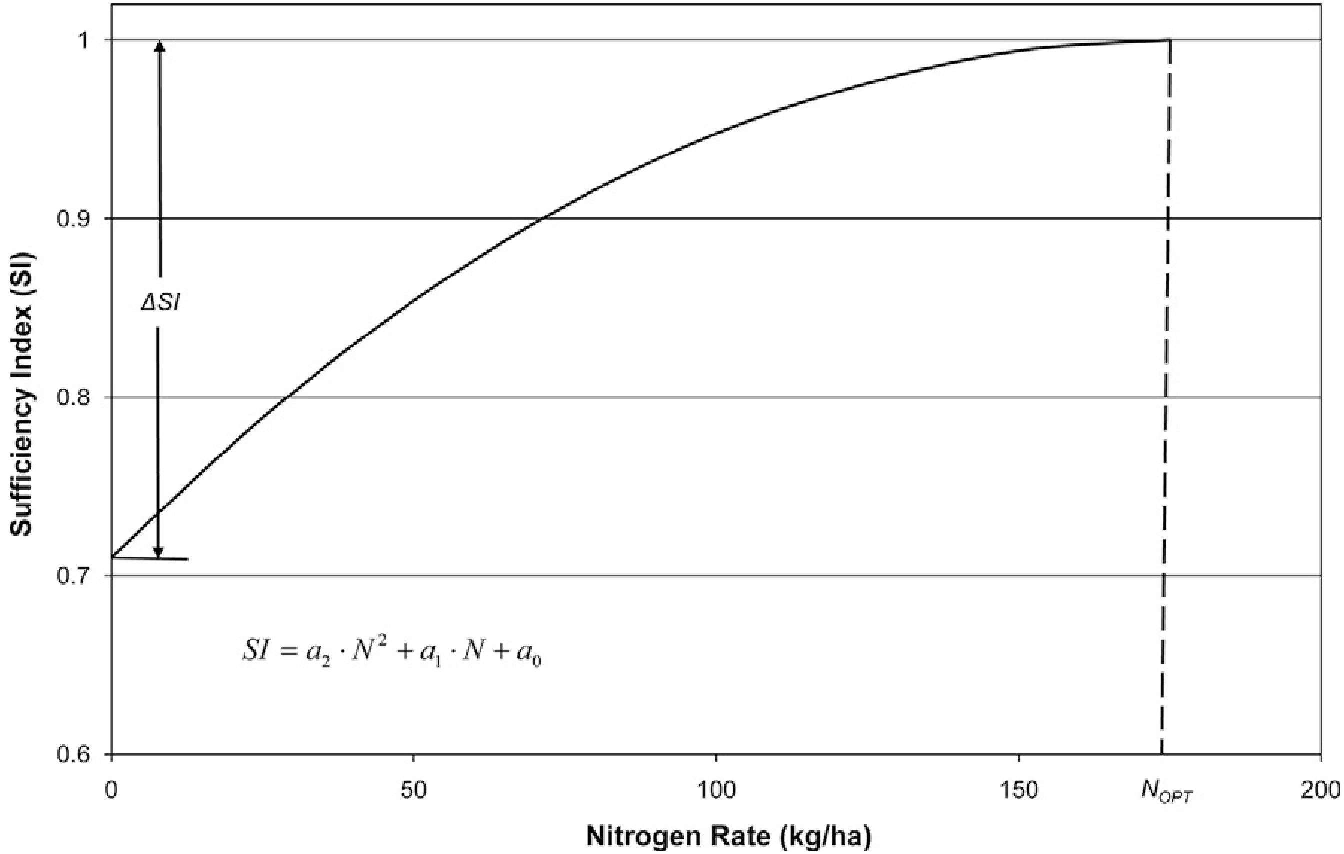
$$Nrec = 250 * (ISR_{target} / ISR_{reference}) - 200$$



Kitchen, 2016

Holland–Schepers

Nrec = (N opt - N cred) * SQRT((1 - SI)/ΔSI)



Holland and Schepers, 2010

Field Crops Research 218 (2018) 126–140

Contents lists available at ScienceDirect

Field Crops Research

journal homepage: www.elsevier.com/locate/fcr

Review

Do crop sensors promote improved nitrogen management in grain crops?

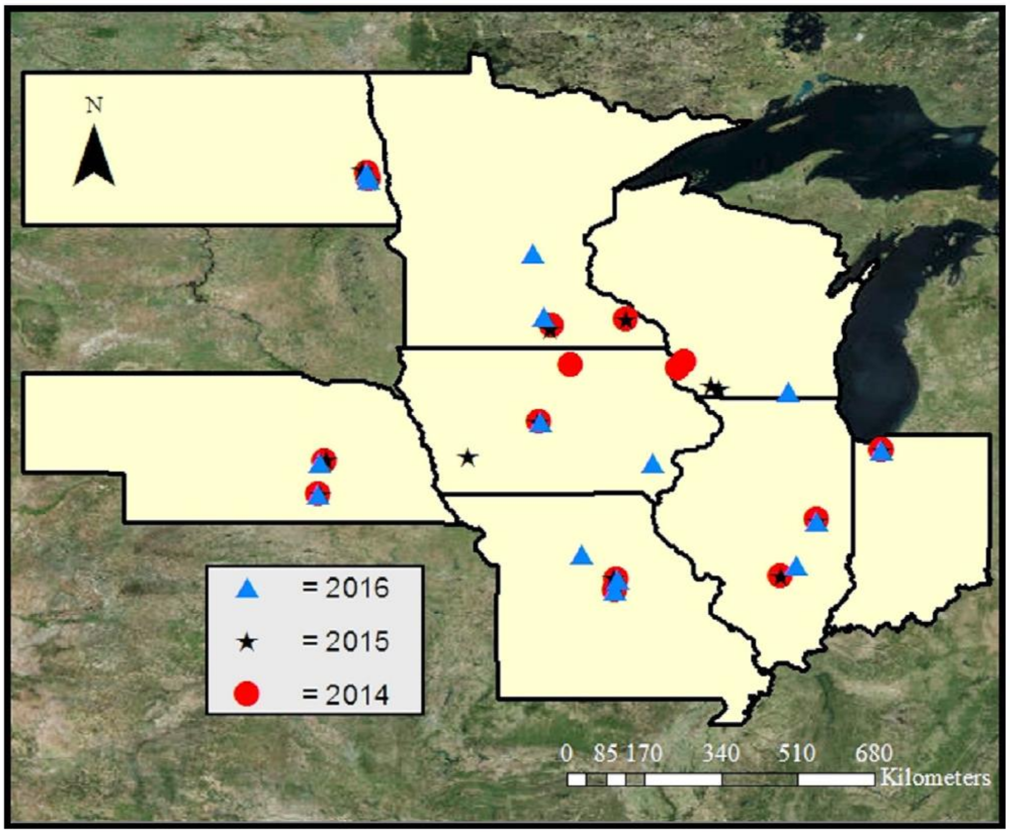
A.F. Colaço*, R.G.V. Bramley

Most studies report N fertilizer savings of 5–45% with little effect on grain yield, but a lack of consistent evidence of economic benefits limits adoption by farmers... Sensor-based N applications which reduced environmental impacts were often not profitable compared to current N practices.

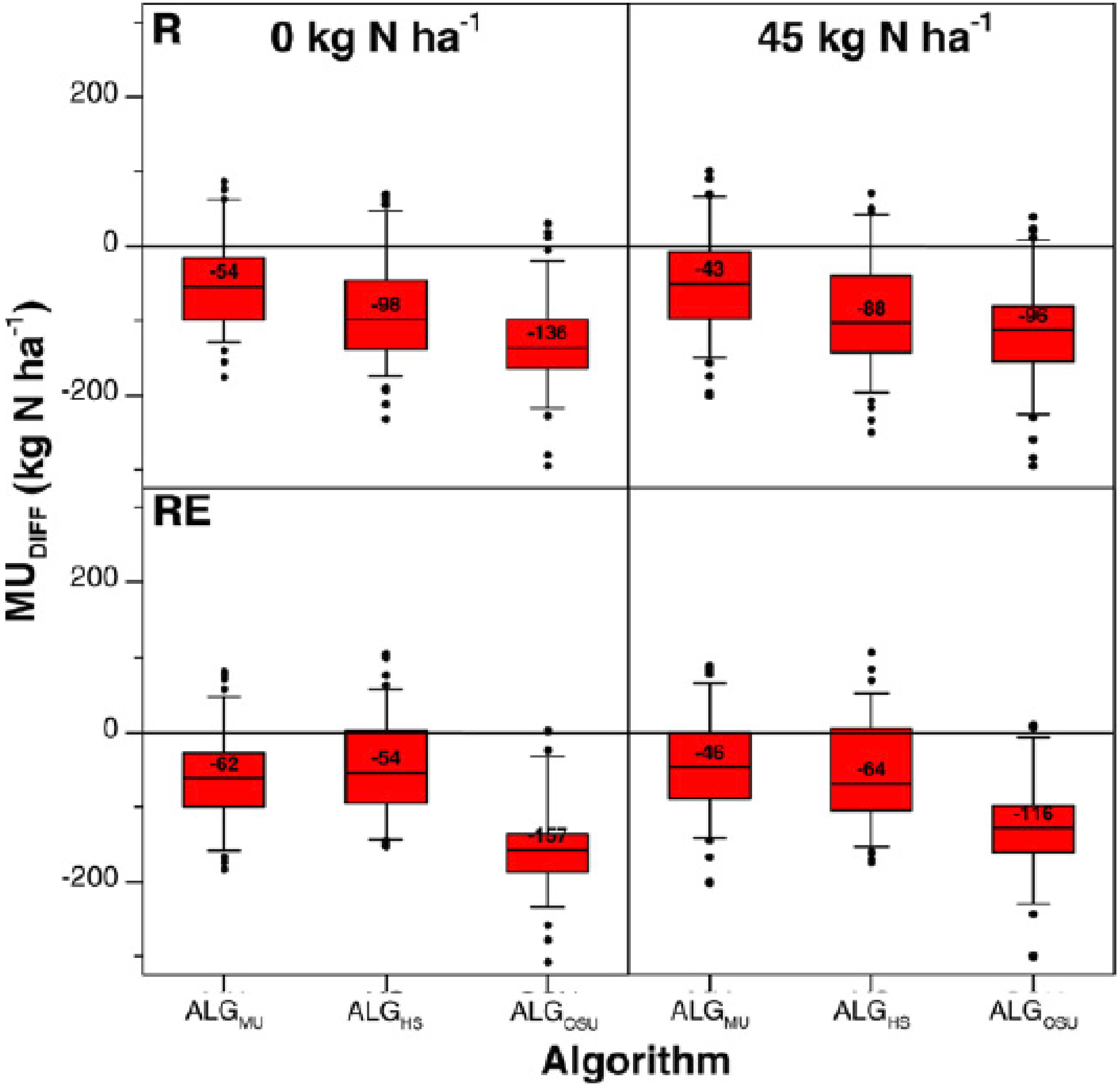
Agron. J. 110:2552–8 (2018)

Active-Optical Reflectance Sensing Corn Algorithms Evaluated over the United States Midwest Corn Belt

G. M. Bean,* N. R. Kitchen, J. J. Camberato, R. B. Ferguson, F. G. Fernandez, D. W. Franzen, C. A. M. Laboski, E. D. Nafziger, J. E. Sawyer, P. C. Scharf, J. Schepers, and J. S. Shanahan



Bean et al., 2018



Bean et al., 2018

“This research demonstrated that AORS algorithms developed locally (i.e., within a US state) often will not perform well when its use is scaled to reach a greater region than the data used to develop the algorithm originally included.”

“This outcome demonstrates that for an algorithm to be utilized over a broad region, development would be best if done employing datasets that give context representing the range of soil and weather conditions.”

Bean et al., 2018

How to Improve the Algorithms?

Agron. J. 110:2541–2551 (2018)

Improving an Active-Optical Reflectance Sensor Algorithm Using Soil and Weather Information

G.M. Bean,* N.R. Kitchen, J.J. Camberato, R.B. Ferguson, F.G. Fernandez, D.W. Franzen, C.A.M. Laboski, E.D. Nafziger, J.E. Sawyer, P.C. Scharf, J. Schepers, and J.S. Shanahan

“We found that adjusting AORS algorithm recommendations with **site-specific weather and soil information** usually resulted in improved N fertilizer recommendations compared to the unadjusted ALG_{MU}.”

Bean et al., 2018

$$NRec_{MU} = \left(280\ \mathrm{kg\ N\ ha^{-1}} \times \frac{ISR_{target}}{ISR_{reference}} \right) - 224\ \mathrm{kg\ N\ ha^{-1}}$$

$$ISR = R/NIR$$

Soil Information

Plant available water content

The difference between the soil moisture at field capacity and permanent wilting point.

SOM

Clay Content

Bean et al., 2018

Weather Information

Growing Degree Days

$$GDD = \frac{T_{Max} + T_{Min}}{2} - T_{Base}$$

Precipitation Evenness

Shannon diversity index

$$\mathrm{SDI} = \left[-\sum \mathrm{pi} \frac{\ln(\mathrm{pi})}{\ln(n)} \right]$$

Where pi = daily rainfall/total precipitation, *n* = number of days in the specified time period being used.

SDI = 1 implies complete evenness (i.e., equal amounts of rainfall in each day of the period);
SDI = 0 implies complete unevenness (i.e., all rain in 1 d)

Abundant and well-distributed rainfall (AWDR)

AWDR = SDI x total precipitation

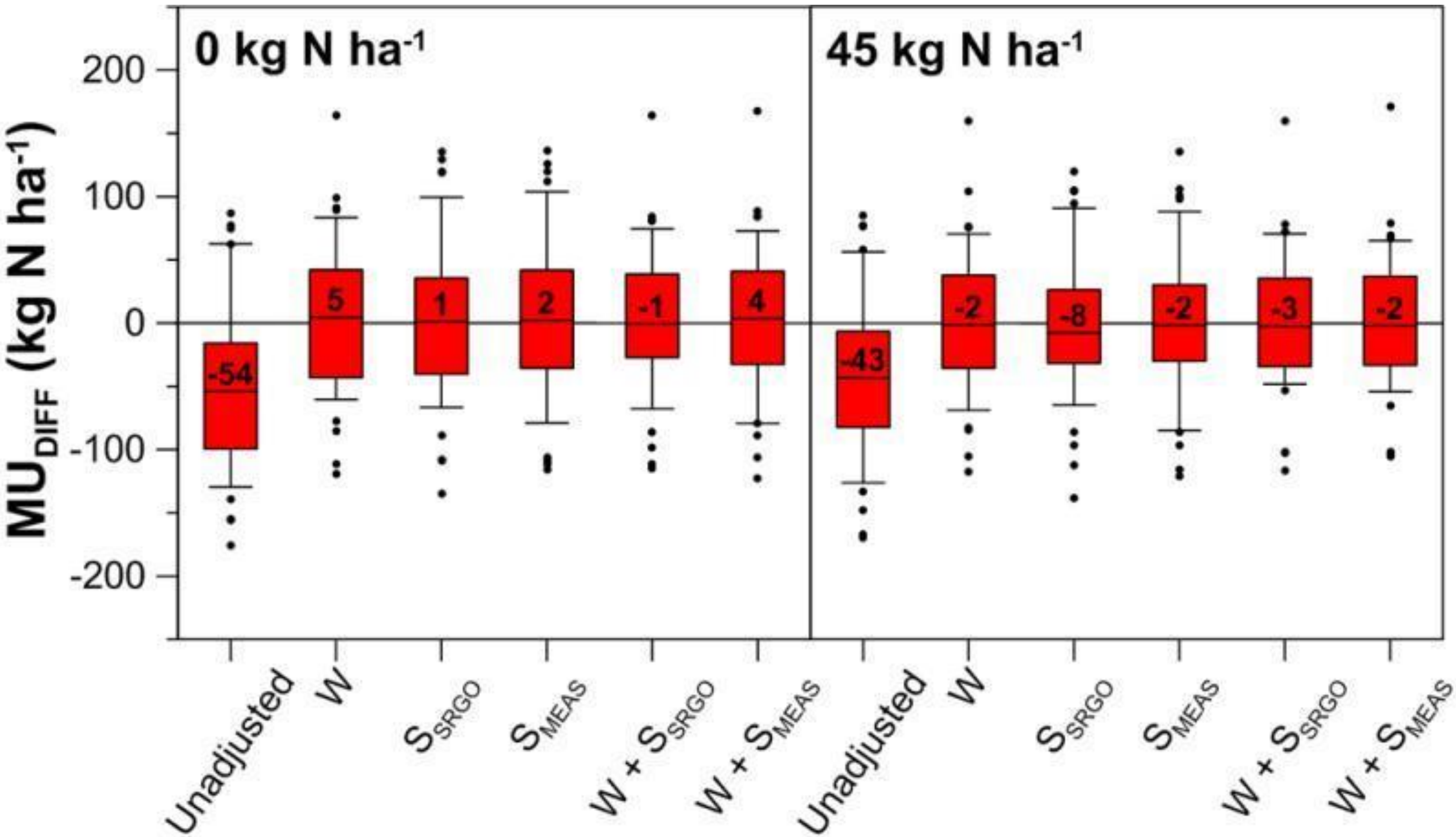
Bean et al., 2018

Table 3. University of Missouri (ALG_{MU}) performance for both at-planting target corn N rates (0 and 45 kg N ha^{-1}) with and without soil and weather adjustments made to the ALG_{MU} nitrogen fertilizer recommendation (Nrec). The root mean square error (RMSE), median of the differences between economic optimal nitrogen (EONR) rate and ALG_{MU}, and the percentage of sites within 34 kg N ha^{-1} of EONR were all used to compare algorithm performances.

Target corn N rate	Adjustment†	Model equation	r^2	p value	RMSE	Median	Sites within 34 kg N ha^{-1} of EONR
kg N ha^{-1}					kg N ha^{-1}		%
0	None	y = Nrec	0.14	0.004	81	–10	20
	W	y = Nrec– 231 + 444 × SDI	0.33	<0.001	58	–11	41
	S_{SRGO}	y = Nrec + 97– 2 × $Clay_{30}$	0.25	0.001	62	2	39
	S_{MEAS}	y = Nrec + 94– 1.7 × $Clay_{60}$	0.26	0.001	62	3	43
	W + S_{SRGO}	y = Nrec– 219 + 492 × SDI– 0.009 × (PPT × $Clay_{30}$)	0.43	<0.001	55	–1	45
	W + S_{MEAS}	y = Nrec– 167 + 400 × SDI– 1.5 × ($Clay_{60}$)	0.40	<0.001	57	–1	43
45	None	y = Nrec	0.12	0.009	73	–43	29
	W	y = Nrec– 211 + 395 × SDI	0.29	<0.001	55	–2	43
	S_{SRGO}	y = Nrec + 85– 2 × $Clay_{30}$	0.23	0.003	57	–8	53
	S_{MEAS}	y = Nrec + 82– 1.7 × $Clay_{60}$	0.23	0.003	57	–2	55
	W + S_{SRGO}	y = Nrec– 200 + 435 × SDI– 0.008 × (PPT × $Clay_{30}$)	0.39	<0.001	50	–3	47
	W + S_{MEAS}	y = Nrec– 201 + 430 × SDI– 0.006 × (PPT × $Clay_{60}$)	0.38	<0.001	51	–2	51

† W, weather; S_{SRGO}, SSURGO soil; S_{MEAS}, measured soil; W + S_{SRGO}, weather + SSURGO; W + S_{MEAS}, weather + measured soil; SDI, Shannon diversity index; PPT, total precipitation from time of planting to time of sensing (mm); $Clay_{30}$, % clay in the upper 30 cm of soil; $Clay_{60}$, % clay in the upper 60 cm of soil.

Bean et al., 2018



Bean et al., 2018

Precision Agric (2016) 17:470–487
DOI 10.1007/s11119-016-9431-3

Evaluation of mid-season sensor based nitrogen fertilizer recommendations for winter wheat using different estimates of yield potential

Jacob T. Bushong[1] · Jeremiah L. Mullock[1] · Eric C. Miller[1] · William R. Raun[1] · D. Brian Arnall[1]

Current nitrogen fertilization optimization algorithm (CNFOA)

Proposed nitrogen fertilization optimization algorithm (PNFOA)

Days of potential growth (DPG)

Adequate temperature along with adequate soil water

Fractional water index (FWI), which is a unitless value that ranges from 0.00 for dry soils to 1.00 for wet/saturated soils

Stress index (SI)

Dividing the amount of PAW by the amount of water needed to maintain yield from the date of sensing to an assumed harvest date of June 10.

Table 6 Model parameter estimates for estimating winter wheat grain yield

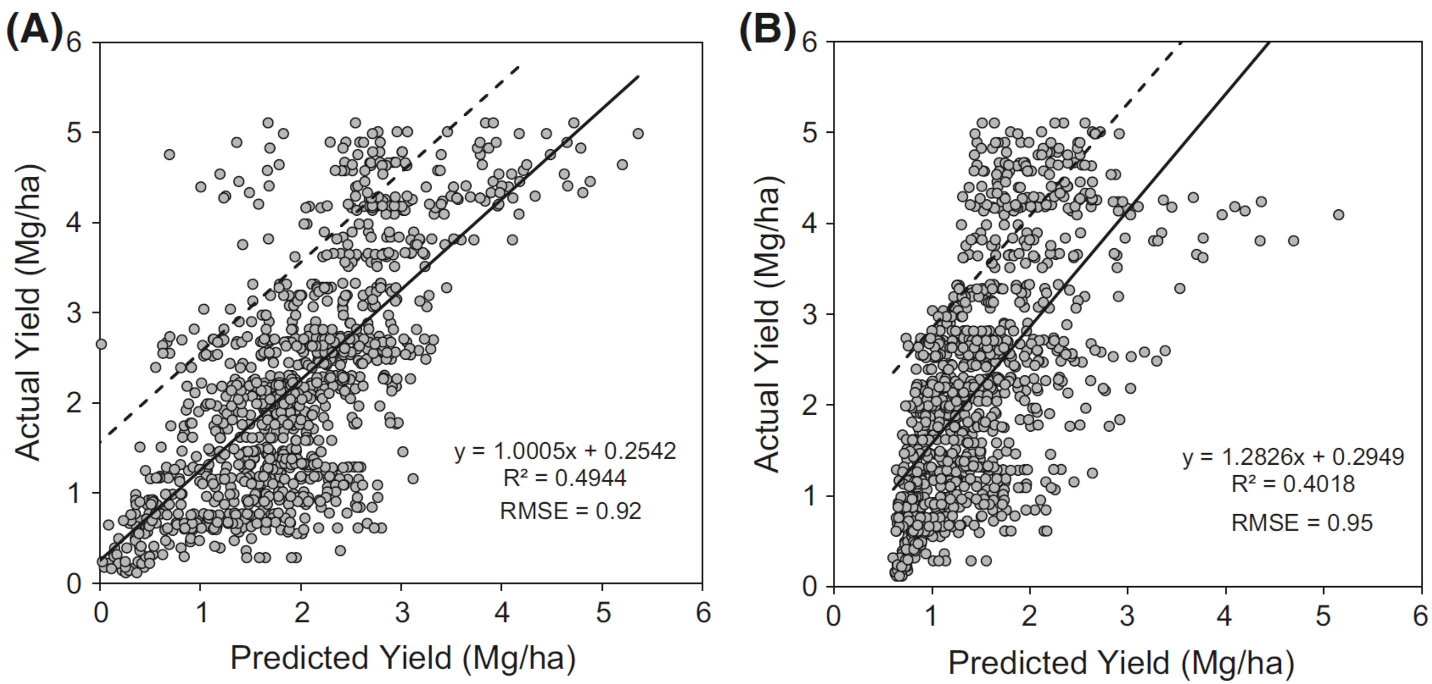
Parameter	All sites		Loamy sites		Coarse sites	
	Est.	Pr > |t|	Est.	Pr > |t|	Est.	Pr > |t|
Intercept	8.32	–	9.62	–	4.68	–
DPG	−0.09	<0.0001	−0.08	0.0320	−0.06	0.1261
SI	−10.66	<0.0001	−13.82	<0.0001	−5.03	0.2157
NDVI	−15.68	<0.0001	−17.17	0.0005	−13.19	0.0356
DPG*SI	0.11	<0.0001	0.11	0.0029	0.05	0.2408
DPG*NDVI	0.22	<0.0001	0.18	0.0051	0.23	0.0014
NDVI*SI	25.80	<0.0001	31.44	<0.0001	16.51	0.0250
NDVI*DPG*SI	−0.28	<0.0001	−0.27	<0.0001	−0.22	0.0064

DPG days of potential growth, *SI* stress index, *NDVI* normalized difference vegetative index

Bushong et al., 2016

Improved Model

Current Model



Feekes 5–10

Fig. 4 Linear relationships between predicted winter wheat in-season estimations of yield based upon soil moisture parameters (A) or the current model (B) used to predict actual grain yield. Data presented is from all validation sites across all growth stages. Dashed line represents one standard deviation above the actual yield

Bushong et al., 2016

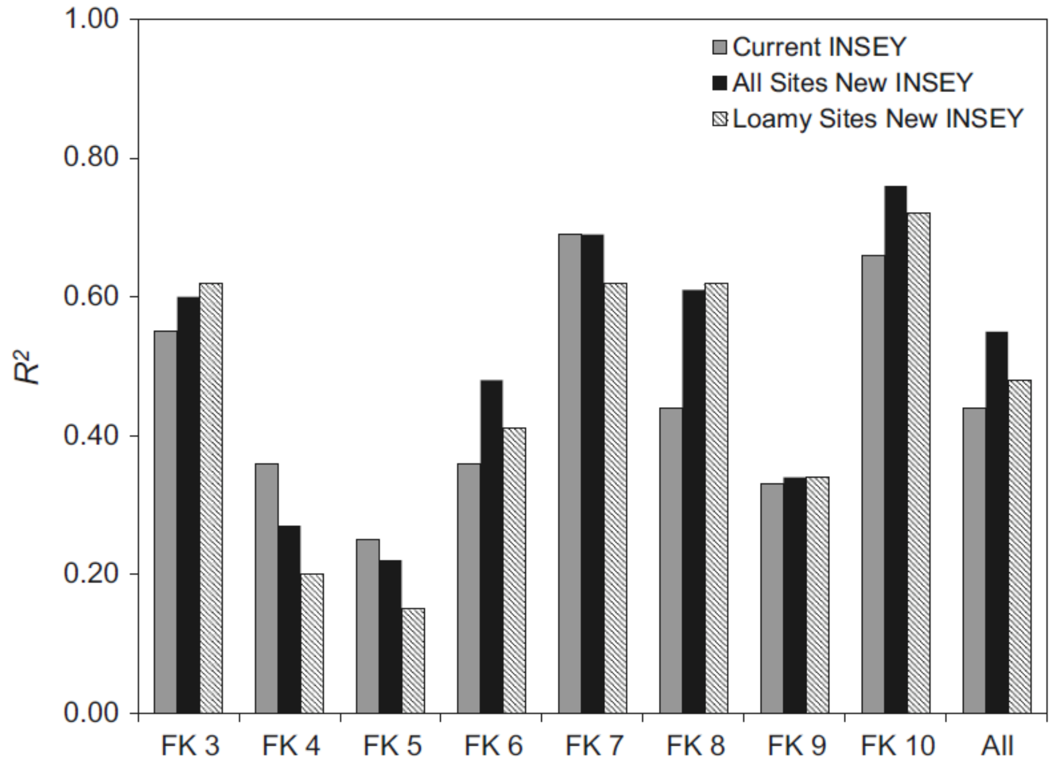


Fig. 1 Validation sites with a loamy surface soil texture coefficient of determination (R^2) values for the current model of determining winter wheat in-season estimation of yield (INSEY), and proposed new models that incorporate soil moisture data into yield prediction. Two proposed new models are displayed, one that predicts yield regardless of soil type and one that predicts yield for soils with a loamy textured surface. Predictions are grouped together by Feekes (FK) growth stage across the 2012 and 2013 growing seasons

The fact that soil physical properties were incorporated into the SI model parameter for the proposed INSEY model would negate the need for different grain yield prediction models based on soil type

Bushong et al., 2016

Table 5 Coefficient of determination (R^2), root mean square error (RMSE), and percent of sites that predicted N fertilizer recommendations under, over, and within 20 kg N ha^{-1} of agronomic optimum N rate (AONR)

Method	R^2	RMSE	Percent under AONR	Percent above AONR	Percent within 20 kg N ha^{-1}
CNFOA	0.33	37.1	74	26	44
PNFOA	0.32	37.0	76	24	50
GA	0.34	36.8	53	47	41
MGA	0.33	37.1	50	50	41
PPNT	0.11	39.8	50	50	22

CNFOA current N fertilizer optimization algorithm, *PNFOA* proposed N fertilizer optimization algorithm, *GA* generalized algorithm, *MGA* modified generalized algorithm, *PPNT* pre-plant NO_3 soil test

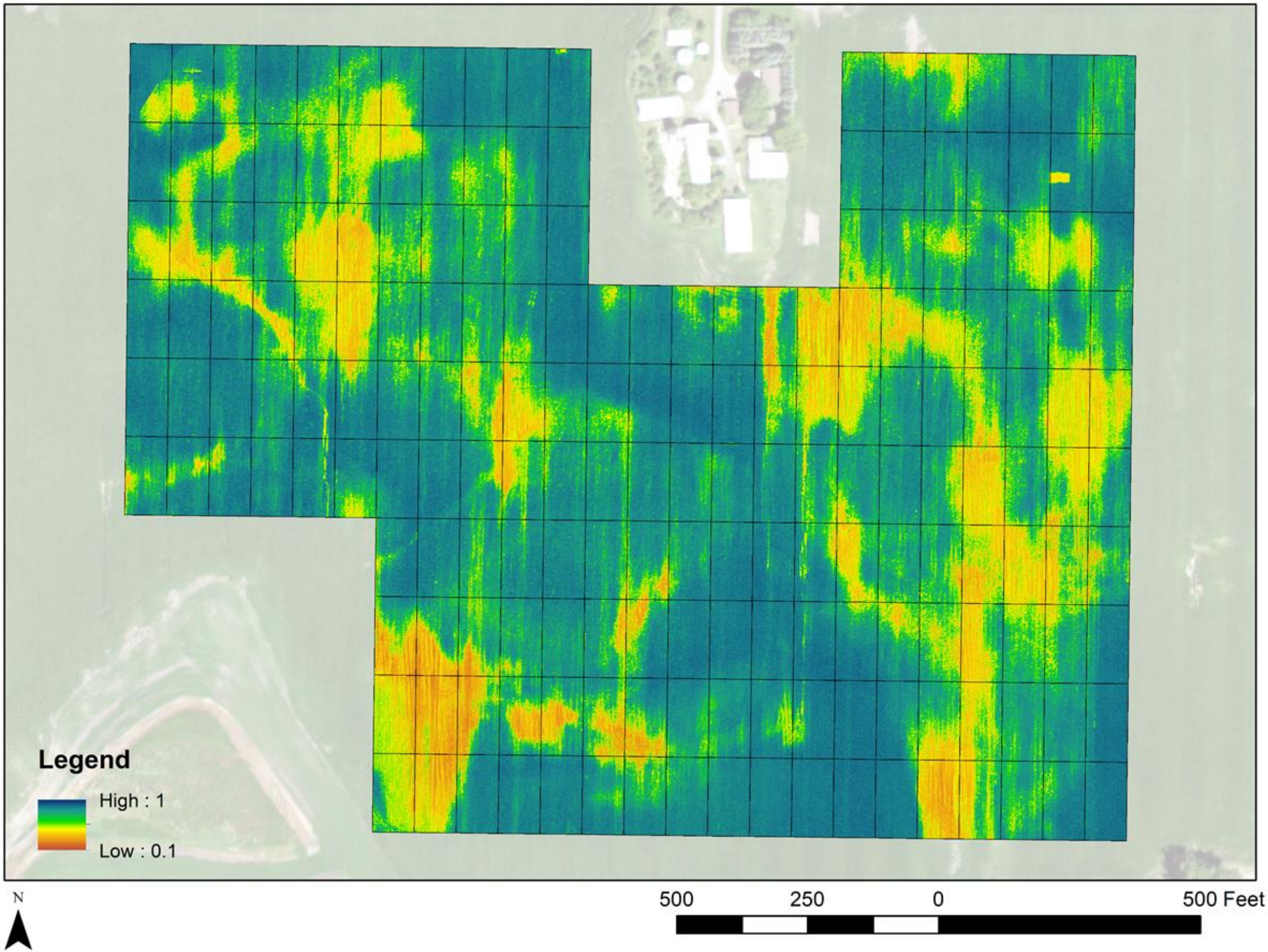
Bushong et al., 2016

On-the-Go Sensing and Variable Rate N Application

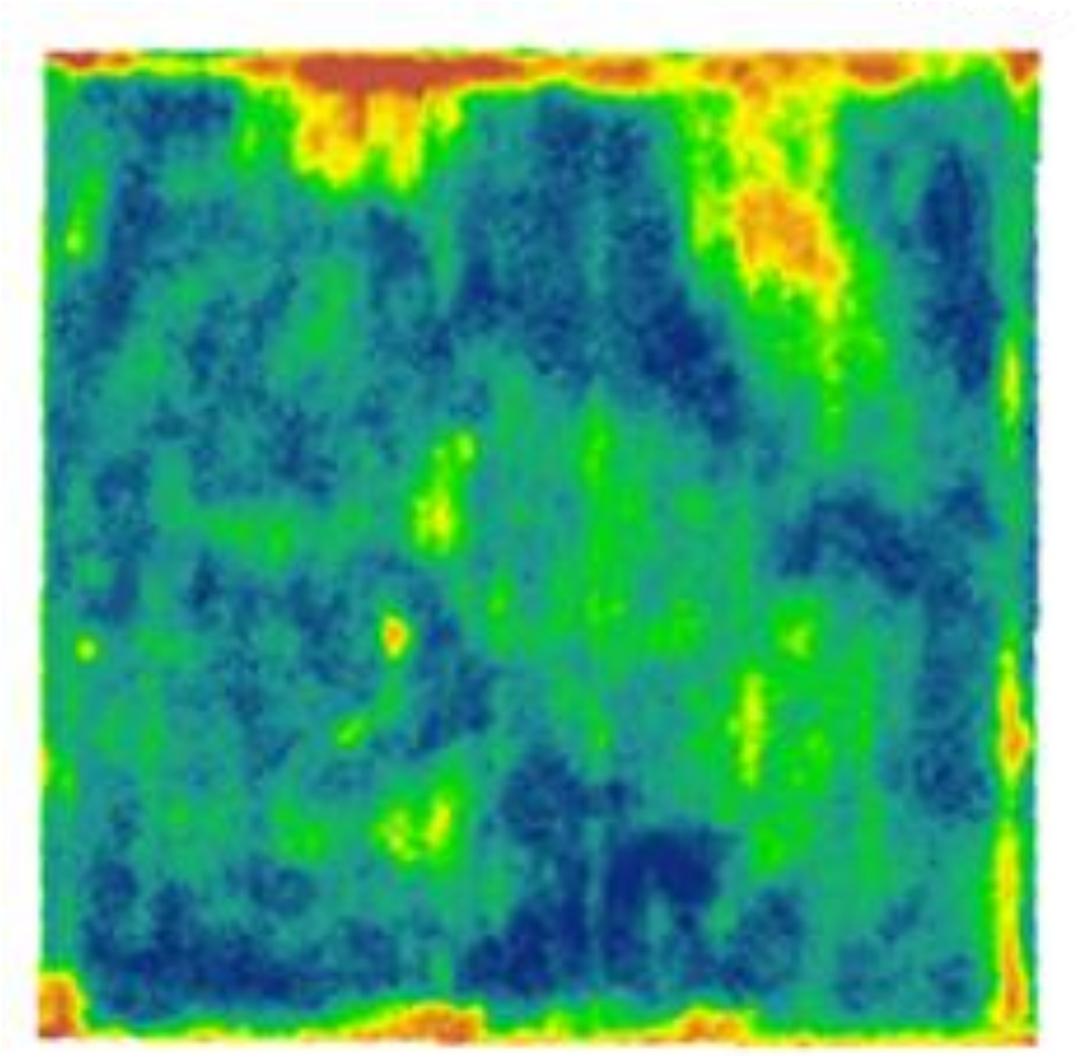
UAV Remote Sensing

AeroVironment™

PROCEED
WITH
CERTAINTY


Legend
High : 1
Low : 0.1
N
500
250
0
500 Feet

planet.



Daily revisit time
~3 m resolution
Four spectral bands (R, G, B, NIR)

Precision Agric (2010) 11:621–635
DOI 10.1007/s11119-010-9188-z

Development and validation of fuzzy logic inference to determine optimum rates of N for corn on the basis of field and crop features

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- **IF** (EC_a is high **OR** ELE is low **OR** SLP is high) **AND** (NSI is low) **THEN** (EONR is high).
- **IF** (EC_a is high **OR** ELE is low **OR** SLP is high) **AND** (NSI is high) **THEN** (EONR is med).
- **IF** (EC_a is low **OR** ELE is high **OR** SLP is low) **THEN** (EONR is low).
- **IF** (EC_a is med **OR** ELE is med **OR** SLP is med) **AND** (NSI is low) **THEN** (EONR is med).
- **IF** (EC_a is med **OR** ELE is med **OR** SLP is med) **AND** (NSI is high) **THEN** (EONR is low).

These rules can be updated to include local knowledge or new experimental results.

Tremblay et al., 2010

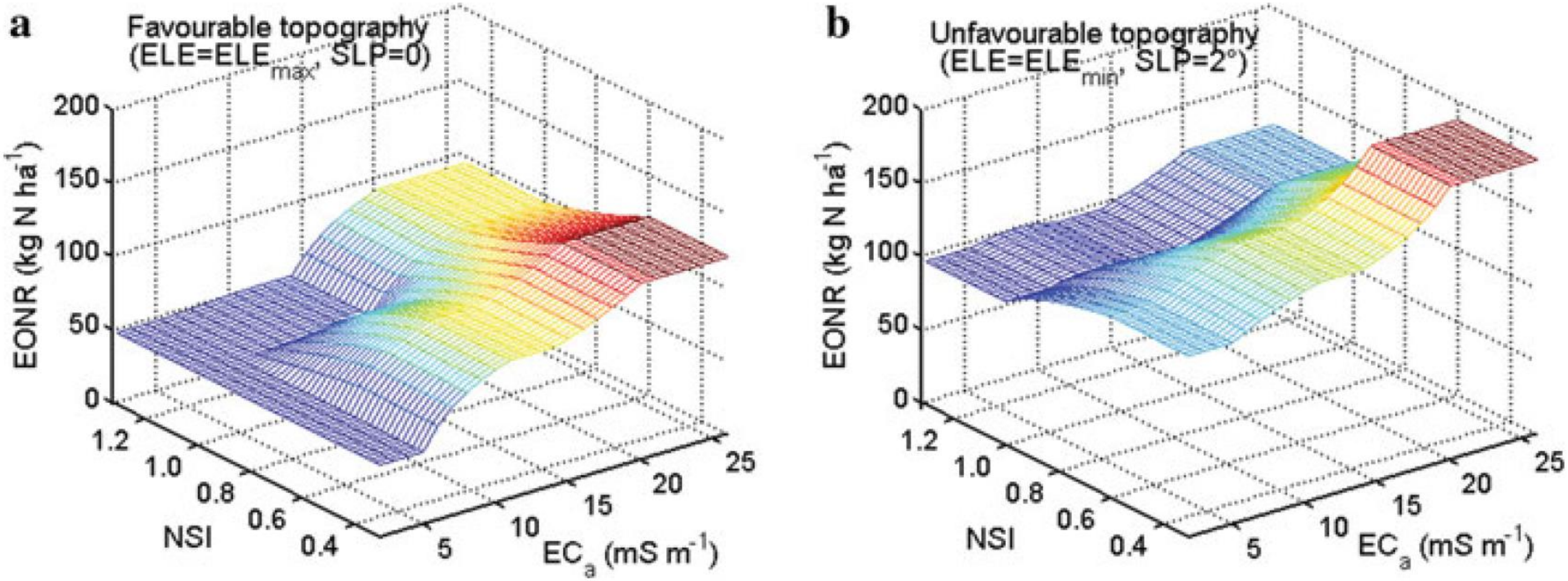


Fig. 8 Simulation of EONR using the FIS developed for different situations of input values under conditions of: a favourable topography and b unfavourable topography

Tremblay et al., 2010

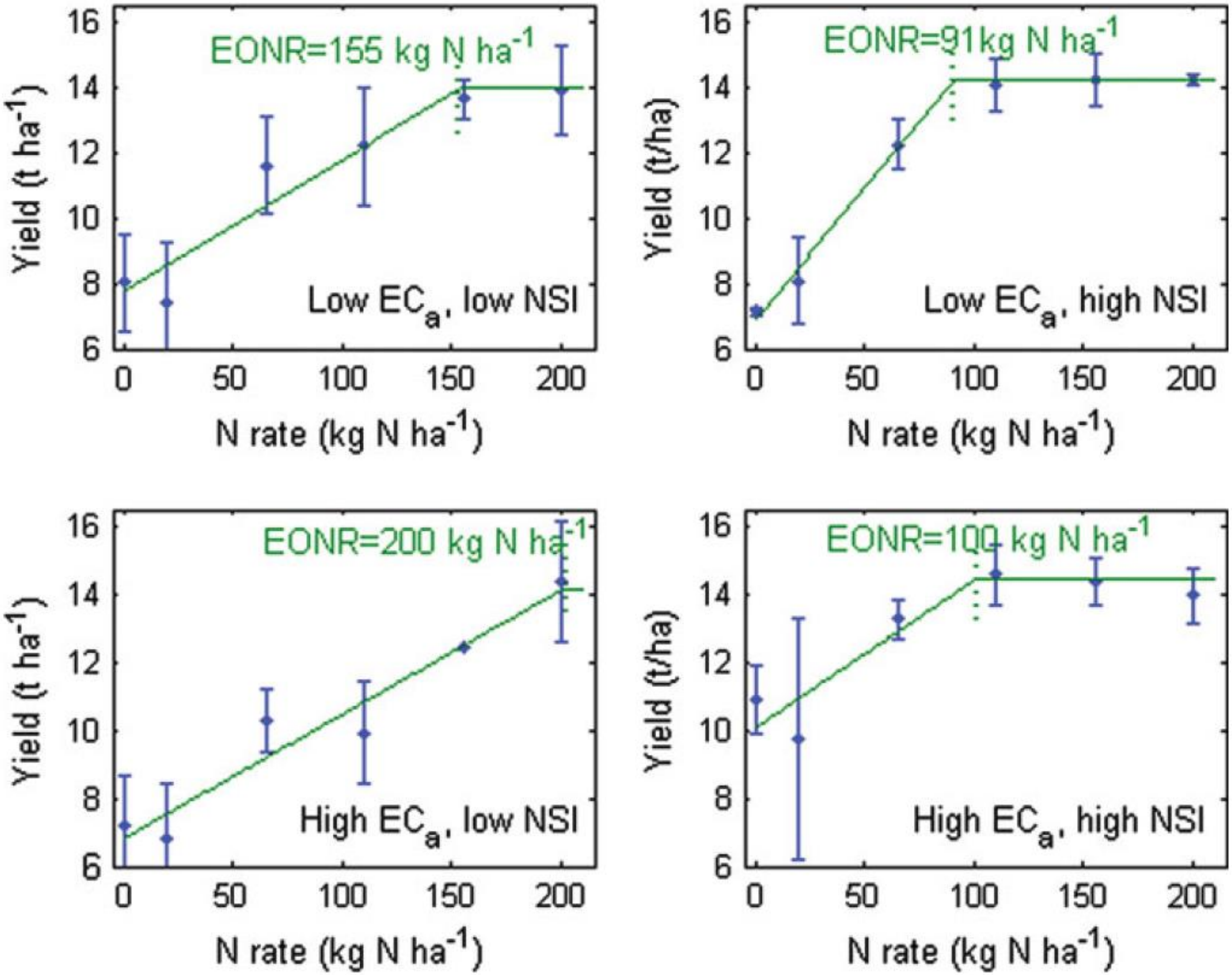


Fig. 9 Actual EONR in 2008 ($EONR_{val}$) from a linear-plateau model according to four combinations of EC_a and NSI levels (low or high)

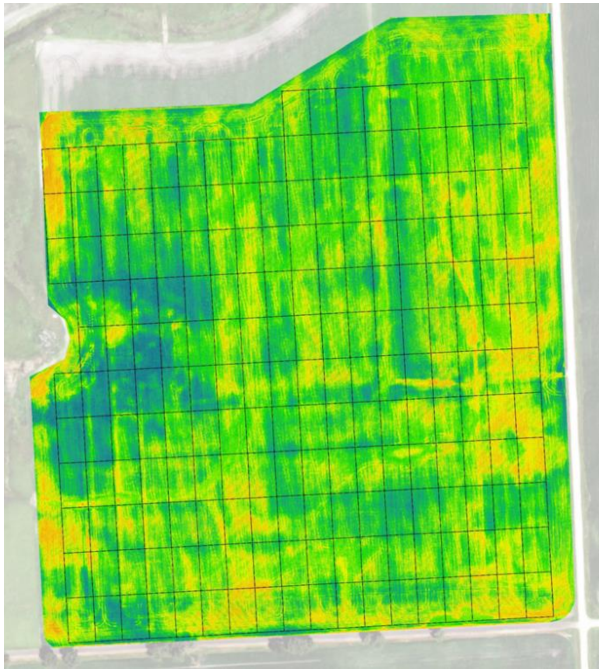
Tremblay et al., 2010

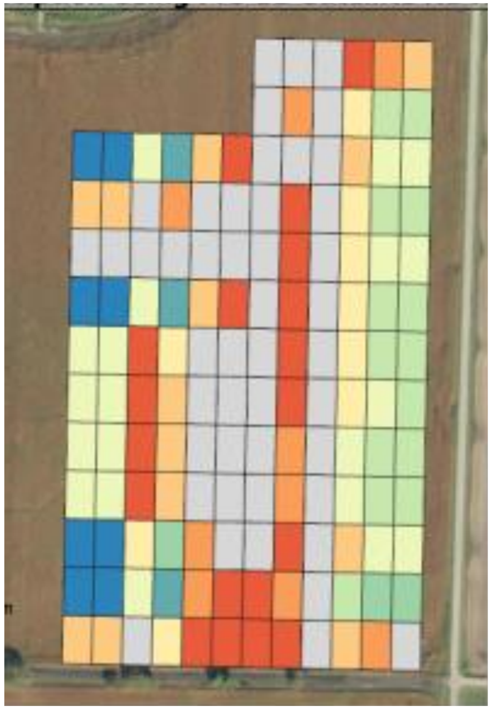
Table 2 Nitrogen rates recommended for the validation (2008) field by the FIS model (FIS = $EONR_{FIS}$), the provincial guidelines (CRAAQ) and the grower's agronomist (Grower), together with actual EONR for each of the four EC_a–NSI combinations (Val = $EONR_{val}$)

EC_a–NSI combination	N rate (kg N ha^{-1})				Grain yield (t ha^{-1})			
	FIS	CRAAQ	Grower	Val	FIS	CRAAQ	Grower	Val
Low EC_a–low NSI	160	170	135	155	13.9	14.0	13.1	14.0
Low EC_a–high NSI	99	170	135	91	14.1	14.2	14.2	14.2
High EC_a–low NSI	190	170	135	200	13.6	13.0	11.3	14.1
High EC_a–high NSI	112	170	135	100	14.4	14.4	14.4	14.4
Global (all cases)	129	170	135	–	14.0	14.0	13.2	–

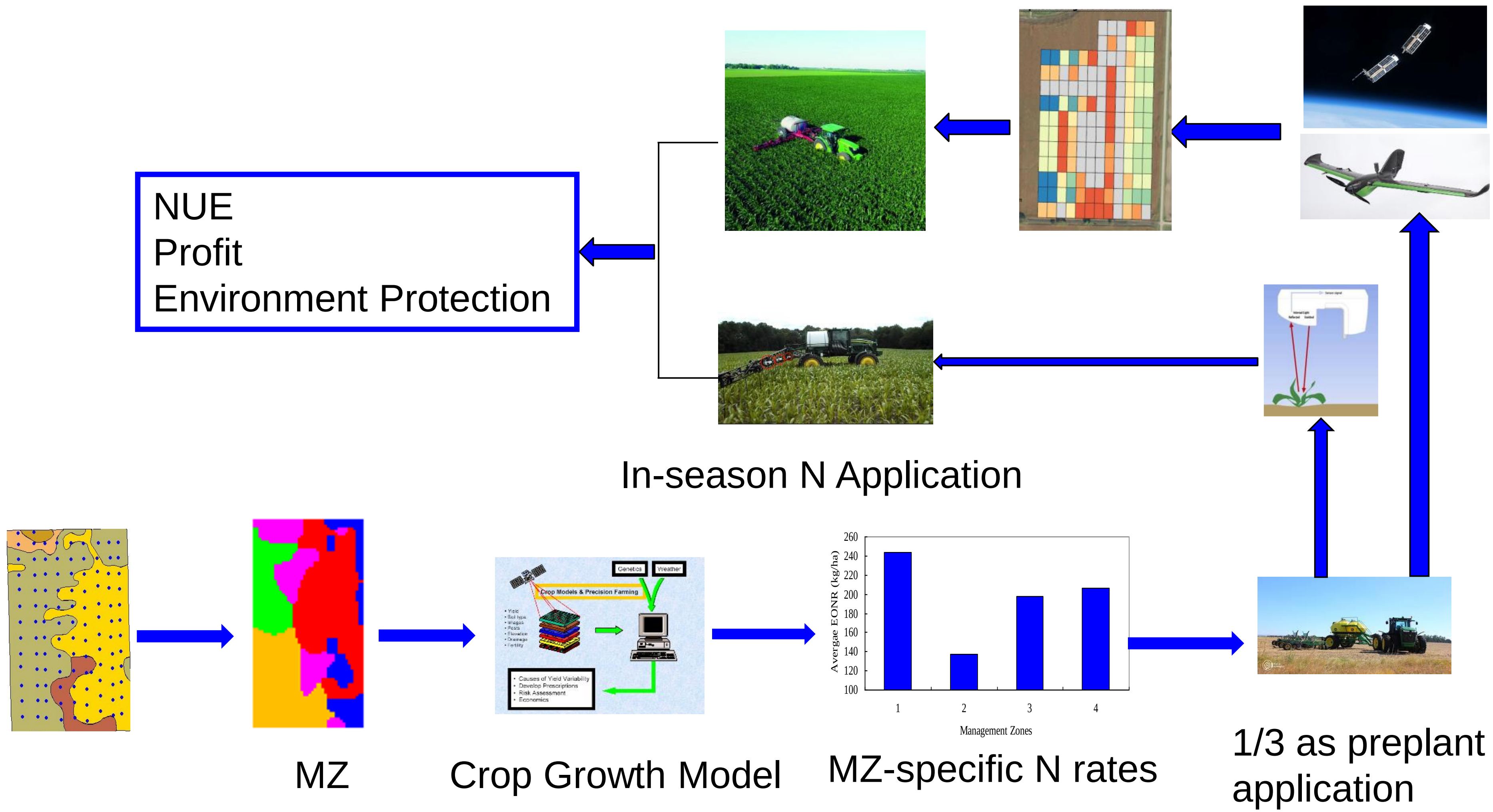
Tremblay et al., 2010

Remote Sensing-based In-season N Recommendation Technology



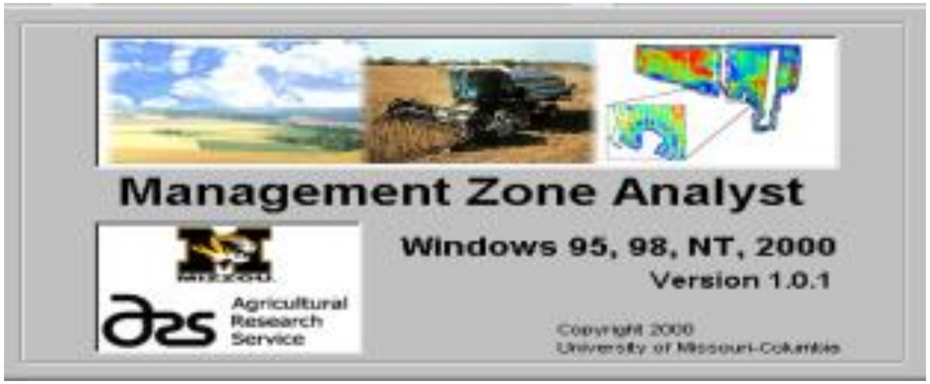


An Integrated Precision Nitrogen Management Strategy



Discussion Time

Management Zone Delineation Methods



SOFTWARE

Management Zone Analyst (MZA): Software for Subfield Management Zone Delineation

Jon J. Fridgen, Newell R. Kitchen,* Kenneth A. Sudduth, Scott T. Drummond, William J. Wiebold, and Clyde W. Fraisse

Fuzzy K-means Clustering Algorithm

Fuzziness Performance Index (FPI)

A measure of the degree of separation (i.e., fuzziness) between fuzzy *c*-partitions of **Y**

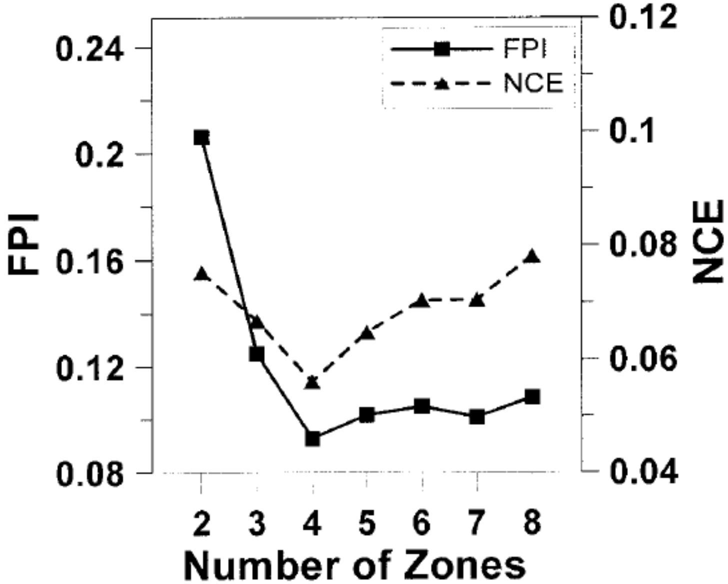
FPI = 0 - 1

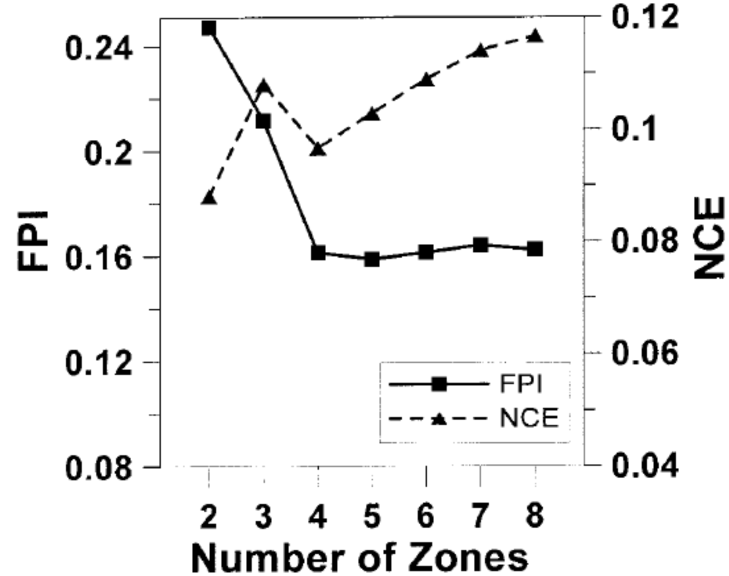
Normalized Classification Entropy(NCE)

Models the amount of disorganization of a fuzzy *c*-partition of **Y**

How to Determine the Optimum Number of MZs?

The optimal number of clusters for each computed index is when the index is at the minimum, representing the least membership sharing (FPI) or greatest amount of organization (NCE) as a result of the clustering process.





Fridgen et al., 2004. Agronomy Journal

Establishing Management Classes for Broadacre Agricultural Production

J. A. Taylor,* A. B. McBratney, and B. M. Whelan

Agron. J. 99:1366–1376 (2007).

PROTOCOL

1. Clean-Up, Trim, and Transform the Data

2. Spatial Prediction of the Data

VESPER

3. Generating Management Classes

FuzME

4. Determining the Optimum Number of Management Classes

5. Validating the Management Classes